



CASCADING EFFECTS OF FUEL NETWORK INTERDICTION

THESIS

MARCH 2015

Jeffrey Thomas Painter, MAJ, US Army

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**DEPARTMENT OF THE AIR FORCE
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Major, USA

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Abstract

This thesis develops the Fuel Interdiction and Resulting Cascading Effects (FI&RCE) model. The study details the development and experimental testing of a framework for assessing the interdiction of a refined petroleum production and distribution network. FI&RCE uses a maximum flow mathematical programming formulation that models the transit of fuels from points of importation and refinement through a polyduct distribution network for delivery across a range of end user locations. The automated model accommodates networks of varying size and complexity. FI&RCE allows for parameters and factor settings that enable robust experimentation through implementation in MATLAB 2014 and the commercial solver CPLEX (Version 12.5). Experimental design allows the investigation of interdiction or disruption on supply and network infrastructure locations in order to support the strategic analytical needs of the user. Given a target set, FI&RCE provides measured responses for the resulting fuel availability and a valuation of economic loss. The value of economic loss feeds a Leontief based input-output model that assesses the cascading effects in the studied economy by implementing a mathematical program that optimizes the remaining industrial outputs. FI&RCE demonstrates a framework to investigate the military and cascading effects of a fuel interdiction campaign plan using a realistic case study.

I am always grateful for the generosity of my heavenly father, who bestows upon us all the blessings of this life and guides every aspect of my research. I would like to express my sincerest appreciation to my wife and children for their patience and fortitude as my partners in our unique and challenging journey of life. I would like to thank my parents for their unwavering support.

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Jeffrey Thomas Painter

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CASCADING EFFECTS OF FUEL NETWORK INTERDICTION

I. Introduction

1.1 Background

Refined petroleum distribution networks are the economic lifeblood of the United States and many other countries. The network that provides the commodities essential to modern life is transparent to most consumers. Nearly every refined product consumed in the US is delivered via a complex pipeline network. The gasoline, diesel, and heating oil that sustain American quality of life generally only travel by truck from a local distribution hub to the end user or retail location a few miles away (Cafaro and Cerda, 2004:3). The efficiency of a petroleum pipeline system enables its presence in much of the world for use in oil and gas production and downstream delivery of refined products.

Despite their efficiency, these distribution networks have demonstrated historically significant vulnerability. Military organizations are particularly dependent on petroleum. The US Department of Defense is among the world's largest organizational consumers of refined petroleum (Schwartz *et al.*, 2011) and maintains its own complex distribution network. The petroleum requirements of modern warfare have enticed the targeting strategies of military planners since at least the beginning World War II. Early examples of this include the oil plan that emphasized the targeting of Germany's refinery and synthetic fuel operations in Eastern Europe while the transportation plan affected German railway networks that delivered the refined products (Mark, 1992: 226). By September of 1944, the Allies had reduced production of aviation gasoline required by the Luftwaffe, decreasing German refinery output to less than 55% of military requirements (Hall, 1998: 226-227). In the Pacific Theater, the combination of anti-ship mines, aerial bombardment, and naval interdiction to include US submarines reduced

the oil imports of Imperial Japan to a negligible level by the beginning of 1945 (Yergin, 1992: 358). By the time Curtis LeMay's B-29s attacked the Japanese refinery and distribution networks beginning in May 1945, there was little ongoing production left to impede due to the strangulation of raw materials (Hall, 1998: 330).

The Allied Forces of World War II were equally innovative in the delivery of refined products to their own Armies, which compromised half of all war stocks shipped across the Atlantic. The adoption of standardized octane levels in vehicle development reduced the required number of fuel products to a single blend each of gasoline and diesel. A complex pipeline system deployed from England to forward combat areas bypassed the heavily taxed truck transport system known as the Red Ball Express. Truck shipments that did occur utilized the German-designed 5-gallon fuel jug (the ubiquitous Jerry can) that could be efficiently transferred by a single soldier between vehicles and units (Yergin, 1992: 382). The only widely documented fuel shortage that significantly impacted Allied operations beyond the initial Normandy beachheads famously occurred when the Allied Ground Force overextended its lines of communication during the rapid breakout of Northern France in August of 1944. Most operations ground to a temporary yet strategically critical halt, particularly in the Third Army sector under Patton. The strategic ramifications of the fuel prioritization policies amongst the Allied Armies during this period are still debated by historians (Yergin, 1992: 386-388).

The Suez Crisis in 1956 demonstrated the liability of reliance on petroleum tanker maritime traffic during the Egyptian seizure of the Suez Canal. More significantly, this crisis also provided an early example of the inherent insecurity of pipeline systems when Syria prevented the flow of oil through the Iraq Petroleum Company's pipeline (Yergin, 1992: 496). The net impact of this aspect of the Suez conflict was the demonstration of global dependency

on petroleum stock supplies and the vulnerability of the world economy based on production location in the Middle East and known delivery methods.

The United States Government implemented an oil embargo as a strategic tool against Moammar Ghaddafi's regime in Libya during the lead up to Operation El Dorado Canyon in 1986. The implementation of this embargo was two-fold. President Reagan capitalized on the abundance of supply in the world oil market to justify the economic risk of banning imports of Libyan crude. Additionally, the State Department invalidated the passports of all American citizens in Libya to include oil company employees and executives (Stanik, 2003: 70). The diplomatic goal of these boycotts was to limit US economic investment in Libyan oil at a time when crude consuming states enjoyed a global surplus. These actions successfully reduced oil traded to the US from Libya to less than one-third of its previous level and served as a diplomatic precursor to multiple military strikes (Stanik, 2003: 68).

More recently, the Gulf War in 1991 saw the deliberate interdiction of much of Iraq's downstream capacity including the targeting of 28 refinery locations. Planners specifically limited the duration of humanitarian consequences by avoiding the complete destruction of refineries and abstaining from the targeting of crude production. However, this strategy still caused major outages in electrical production and lengthy interruptions in the availability of gasoline, cooking and heating fuels, and other civilian commodities. While the Gulf War did not last long enough to exhaust Iraqi military fuel stockpiles, the hardships inflicted on the civilian population endured well after the cessation of hostilities (Hall, 1998: 594).

The United States and its allies do not monopolize the ability to interdict petroleum networks. A terrorist attack on the Abqaiq oil field owned by Saudi Aramco failed to achieve an effect on production, but did cause the world oil markets to spike by over \$2 per barrel (Al-

Rodhan, 2006: 2). Although the extensive layers of security thwarted the complex attack, the event compelled the Saudis and other major producers to reassess and expand the physical protection of their vast networks from increasingly emboldened extremist organizations. A successfully executed attack on a large producer such as Saudi Arabia or a centralized production and transport center such as Al-Shuaiba in Kuwait could have global ramifications by impacting a significant portion of daily production. A similar circumstance occurred recently when Kuwait's oil refineries went offline due to a localized power outage in January 2014 (Reuters, Kuwait, 2014).

1.2 Problem Statement

A petroleum product distribution network may be vulnerable for a variety of reasons. Conflict, natural disasters, economic conditions, and man-caused environmental catastrophes have all contributed to the disruption of petroleum network flow. The occurrence of such disruptions is well-known and documented. Additionally, modern military air power has shown a vast ability to effectively interdict these networks as described in Section 1.1. The cascading effects are more difficult to assess and analyze. The impact of network disruption could follow an aerial interdiction campaign or a natural disaster such as a hurricane. Strategic planners require the appropriate methodology and tools to determine how an interdiction or disruption incident will affect local and global markets in terms of the immediate impacts and cascading effects. Military planners may require the ability to interdict the petroleum supplies of an armed adversary without crippling the local economy and quality of life. Strategists may also intend to minimize impacts on the global economy and commodity trades.

The problem statement has two primary components. First, how would the interdiction of a refined petroleum distribution network impact the delivery of energy products to the end

user? What end users would suffer the greatest impacts in functionality? The second component considers other effects of these impacts. What cascading effects would manifest throughout the economy of the country or region in question? How would these effects impact the productivity of various industries in the country analyzed?

These components form the basis of the network evaluation outcome: How can military planners interdict a petroleum network in order to limit the availability of refined products to an adversary while controlling the magnitude of collateral economic and civil impacts both locally and around the globe?

1.3 Methodology

The methodology utilized includes development of a petroleum network model that considers multiple factors that are common to the distribution networks of refined petroleum throughout the world. This proposed model includes refineries, storage facilities, and transportation networks using various supply methods, distribution points, and delivery parameters. The proposed model includes a mathematical programming implementation that enables the user to experimentally interdict components of the petroleum product network in a manner consistent with the desired contingency.

The network methodology provides insight on the immediate impacts on product flow through the network given disruptions within the network that are characterized as nodes or edges. The proposed network representation predicts the impacts of interdicting the network and extends the results to estimate cascading effects. This requires consideration of the supported economy and the affected network structure. The methodology generates an estimate of the reduction in refined product flow to various locations in the interdicted network. Additionally, the approach must assess the network for an appropriate amount of time specified

by the user and update the conditions of the system appropriately. Given the assessment of the degradation of network flow capacities, the results inform an input-output model that estimates the magnitude of cascading second and third order effects throughout dependent industries.

Because the flow of refined petroleum products is completely integrated into so many other industries, the expected decline in availability is essential to determination of these cascading effects. Examples of industries that directly rely on these products include transportation, power generation, agriculture, and mining. In a modernized society, almost every other element of the national economy and daily life is affected to some degree by the availability of energy. In lesser developed societies, the absence of consistent electrical grids and other basic utilities may be commonplace (Yergin, 1992: 634-635).

Follow on modeling presents potential solutions to estimate cascading effects. The effects are grouped into market effects including energy price fluctuations, corporate effects, and industry productivity effects. Network effects estimate the impact on the system including storage depletion, distribution corrections, and end user availability.

The contribution of this study is to extend the commodity flow into follow on industrial applications including electrical generation, agriculture, and transportation. The associated consumer networks include uses in quality of life and labor participation impacts. The commodity flow extends the network from the point of refinement, throughout the distribution, and ceases when the end user consumes the commodity. The finalized methodology allows the evaluation of the cascading effects on the end user based on commodity availability and price. The analytical results differentiate which user requirements remained unmet and which users, including critical strategic locations, obtain sufficient refined petroleum commodities.

1.4 Assumptions and Limitations

The primary assumption supporting this approach is access to highly precise data regarding the economy and petroleum network under consideration. This assumption is limited by the availability of this type of data. The specifics of petroleum production are often a closely held secret. Statistics and production figures available from various sources are often estimates of information that is considered state or corporate secrets by the producer (Inkpen and Moffett, 2011: 388). Data sets developed from open source publications require augmentation to allow for a reasonable assessment of the network capacities in order to estimate essential elements that are not otherwise available. These augmentations can result from criteria based selections, engineering formulations, or from generalized values that are consistent with parameters found within refined petroleum networks that exist worldwide.

The model does not influence the supply and availability of crude stocks. Although the availability of crude supplies to refiners may change substantially within the context of the larger problem, the model assesses interdiction of the product distribution network with the assumption that the flow of crude stocks remains sufficient. Because of the vast availability of petroleum stocks, the number of potential suppliers, and the hesitancy of state actors to intentionally target raw petroleum due to adverse effects to the raw source and the environment, this network begins at the point of refinement and assumes a consistent supply of crude reserves from current or future sources (Inkpen and Moffit, 2011: 11-19).

The demand levels within the network are set at a constant that is determined from the pre-interdiction levels. This assumption is necessary to implement an aggregate model and is based on the shadow demand that will exist in the event that the network cannot achieve known demand levels. Additionally, this is an essential simplifying assumption for the Input-Output

model that requires consistency within the interactions generated by import-export market forces.

The major limitation to this approach is its estimation of conditions at system capacity. The model determines how the multi-commodity network will perform given conditions that maximize its flow rate, particularly to selected critical nodes. The interest of the modeler is to measure how interdictions to the network impact the delivery and availability of supplies. In order to isolate the effects of the interdiction, it is necessary to remove the efficiency parameters that would otherwise determine the most lucrative shipping plan for the network manager. The network manager instead seeks to maximize flow based on network capacities in anticipation of or reaction to a disruption.

An additional limitation is that the model is best suited to a national oil company with complete process control of the hydrocarbon market from crude development through retail sale. Fortunately, this structure is present in most national oil companies (NOCs), which control 90% of the world reserves and dominate the downstream infrastructure of many regional economies (Inkpen and Moffit 55-63). This may not be a serious restriction to a state run system in a time of conflict or emergency if there is sufficient reserve capital to maintain or increase production.

1.5 Scope

This model focuses primarily on the middle distillate sector of refined petroleum. Middle distillates include diesel fuel, heating oil, military jet fuels, and most varieties of military grade fuels. Middle distillates are of particular interest due to their military application. Because middle distillates comprise a significant portion of fuel oils and transportation fuel (Inkpen and Moffett, 2011: 456), the proposed network model examines the

effects of a network interruption on these specific sectors. Although these products are of the most military significance, the production and distribution of gasoline is also included in order to provide a credible measurement of cascading effects. The model considers the impacts on the availability of middle distillates along with gasoline and the cascading effects on the electrical generation, heating, transportation, and other critical sectors.

1.6 Summary

The proposed methodology informs a mathematical model that implements a network solution for a relevant case study. This case study uses experimental design to interdict a refined petroleum distribution network and records response data on relevant statistics. These responses are analyzed to determine the types of targets that are most effective at network interdiction. The data also provides the inputs necessary to analyze the significance of cascading effects within dependent networks.

Using the methodology and analysis presented in this study, an analyst may gain insight on how various interdiction strategies will impact a multi-commodity network. Additionally, the use of similar modeling techniques can inform campaign planning and national strategy when considering requirements to deplete an adversary's capabilities or in anticipation of a natural disaster. The estimates of availability and economic losses allow the analyst to gain perspective on the magnitude of cascading effects across a range of industries that are affected by a disruption of petroleum flow. The consolidated results including availability and cascading effects will allow the analyst to provide a decision maker with a complete assessment of the effects of a disruption of refined petroleum flow.

II. Literature Review

2.1 Introduction

A review of the literature identifies a diverse body of applicable operations research techniques and procedures that supports the scope of this research. The distribution of refined petroleum products using network flow models, multi-commodity flow, and optimization of the downstream sector of the petroleum industry are well studied and documented. Additionally, network interdiction appears consistently throughout the literature review in the form of general methodologies and specific applications that are relevant to petroleum network flow and pipeline systems. Although the primary impacts of this type of interdiction are relatively straight-forward, the results are important in the determination of follow on effects. The proposed model requires a suite of tools that will identify the impacts of various contingency events that may interdict the storage, distribution, end users, and supply availability of refined petroleum products in a specified economy. The proposed model will assess cascading impacts in regional industries and global markets. The literature includes extensive research on cascading effects that encompasses the span of critical infrastructure supported by refined petroleum networks. Specific studies enumerate potential impacts on a variety of case specific locations. Finally, there is a breadth of research considering global impacts of petroleum network disruptions.

Many recent publications explore the impact of Hurricane Katrina on the oil and gas industry at refineries in the United States. This information proves useful when considering the global impacts of localized disruptions. Additional studies examine potential market effects of a catastrophic event at a refinery location or distribution hub. These market impacts could envelop the industries of power generation, transportation, consumer energy products such as

heating and cooking fuels, as well as agriculture. The literature review revealed various optimization techniques and other modeling strategies necessary to inform the modeling approach and follow on analysis.

A unique aspect of petroleum production and distribution is the almost universal applicability of operations research to identifying and implementing models and solutions. Optimization applies to refinery mix problems as well as distribution networks. Heuristics, empirical modeling, stochastic modeling, and simulation are all widely utilized tools in the development of transportation network efficiency. Market databases are also required to meet the vast consumer demand for petroleum products in the world economy. International Oil Companies (IOCs) include some of the world's largest refiners such as Royal Dutch Shell and ExxonMobil. National Oil Companies (NOCs) are state owned counterparts of IOCs and control most of the world's petroleum reserves. IOCs and NOCs invest significantly in the tools and expertise required to maximize the profitable output from downstream refinement and delivery operations (Inkpen and Moffett, 2011:465-470). The span of resulting research allows researchers to identify nearly every field of operations research represented in both theoretical instances and applications to actual network disruption. This theme appears consistently throughout the literature.

2.2 Commodity Network Modeling

Network modeling is an essential topic that contributes to the development of the thesis methodology. Network optimization in many forms is a critical component of planning in oil production and refinement capacities. The downstream oil industry is a highly complex supply chain and requires highly efficient and integrated management of its operations in order for producers to gain market advantage (Neiro and Pinto, 2004). More complex operations that

involve both production and refinement require specialized large scale optimization models that trace stock prices and market forces throughout the decision cycle of an international oil company (Inkpen and Moffett: 2011, 442). Network optimization appears prominently in literature regarding the petroleum industry and is heavily utilized and implemented throughout the decision cycle of fossil fuel energy production. An additional application appears in scheduling of production and distribution of these products through a network of limited capacity. The consideration of a network model is essential to determining the impacts and cascading effects due to disruption. Therefore, an appropriate network model should consider a wide range of refinement and distribution capabilities while remaining sufficiently versatile for application in a range of scenarios.

The refined petroleum distribution network of the United States is based almost entirely on an extensive and robust network of liquid fuel pipelines that move products from the point of refinement almost all the way to the point of sale. Shipments travel the last few miles in a truck from the local distribution node to a fueling station where they are accessible to the consumer (Cafaro and Cerda, 2004). A similar supply chain is present in much of the world as NOCs strive for competitive systems of distribution. Rail traffic occasionally supplements interregional pipeline delivery of refined petroleum products. However there are limited global locations with the sufficient rail infrastructure to maintain product flow that is comparable to a major pipeline (Trench, 2001: 2). For this reason, it is unlikely that a rail solution could replace a disrupted pipeline and impossible to achieve with truck transportation. Rail and truck alternatives can provide limited supply capability that is sufficient to maintain a military apparatus in economies where the platforms are available in sufficient numbers. However, the

terminals and road networks necessary to load and transport these platforms are vulnerable to disruption as well.

Refined petroleum products fit a category of problem defined as a multi-commodity flow. The multi-commodity flow problem is described as a supply, distribution, and storage network that is commonly utilized by multiple products. The potential size and complexity of these types of models have increased with the expansion of applications. Robust computational capabilities accommodate the increasing size of these problems, which are increasingly implemented among various industries (McBride: 1998, 33). Familiar petroleum products such as diesel, gasoline, and fuel oil transit common production and distribution facilities from the point of refinement through receipt by the end user. These products each traverse an independent network of storage facilities while sharing common transportation means through multi-product polyduct pipelines (Cafaro and Cerda, 2004).

A mathematical program formulation can represent the multi-commodity flow for N networks of K number of commodities sharing common infrastructure. Each product is modeled as an exclusive sub-network component of the multi-commodity flow. This network requires the construction of a matrix, N , that represents the sub-networks N_1 through N_K as described in diagonal matrix (1). The interactions within N can allow for each network to compete for resources within the a network formulation while utilizing available storage and production capacity (McBride: 1998, 33).

$$N = \begin{bmatrix} N_1 & & & & \\ & N_2 & & & \\ & & \dots & & \\ & & & N_{K-1} & \\ & & & & N_K \end{bmatrix} \quad (1)$$

Software packages are available to solve large multi-commodity network flow problems and can obtain solutions to problem sets with large numbers of variables, nodes, and constraints. Many competing algorithms exist to solve this type of problem program, including those with the CPLEX commercial solver. McBride presents comparisons of commercial algorithm applications, showing viable options for solving industry applications of increasing size (McBride: 1998, 33:35).

Mixed integer linear programs (MILPs) and non-linear programs are highly applicable to petroleum multi-commodity flow because they allow the modeler to determine which elements of the network are operable for a particular product at any given time. Because refineries, pipelines and distribution hubs usually process products sequentially, the MILP allows analysts to specify which elements of the network will handle specific products over an appropriate timeframe using a binary decision variable. This results in a scheduling plan that can accommodate demand and implement the profitable distribution of refined products to the end user that meets the constraints of production runs and product batch availability. Magatao, *et al.* (2006) proposed this framework for use in commodity scheduling across a pipeline network. Cafaro and Cerda (2004) also employed this concept into an integrated network by introducing an MILP that integrates multiple pipelines and products using continuous formulations. This result predicted the effects on depot storage facilities that service a variety of end users. The utility of this function to an interdiction modeler is dependent upon the specificity of available data and the optimization function utilized. Batch scheduling is a necessity in efficient distribution planning, but not essential to a model of maximum flow.

Cafaro and Cerda (2012) consider a technique to develop mixed integer linear or non-linear programs to develop models capable of scheduling and programming the network supply

chain that supports the vast oil and gas demands of the North American consumer. The study detailed a robust optimization model of a mesh-structured pipeline network that resources four oil refined products, four destinations, and a pair of refineries. A mesh-structured pipeline is defined as a network consisting of multiple interconnected distribution systems servicing production sources and providing delivery to various destinations. The mesh-structure also includes storage capabilities that allow for the influx of products into the distribution network as required. The mesh-structure is present in most distribution networks and is particularly applicable for commercial aviation and military airlift where significant amounts of various fuel types require ample storage located along a complex supply chain (Inkpen and Moffet, 2011: 495-496). The formulation includes an iterative list of constraints available from industry on what products can use various transmission nodes and links and in what capacity. This solution enables producers to improve integration of oil production, transportation, and refinement in their planning and decision making (Cafaro and Cerda, 2012).

Neiro and Pinto (2004) provide a generic model of a petroleum supply chain that utilizes mixed integer techniques to optimize supply operations in consideration of the complete process. Their implementation of non-linear techniques allows for additional consideration of the variability in the supply chain and market effects. The article encompasses the process from the point of exploration and traces the commodity stream through refinement and distribution networks that are essential to industry success. Their problem statement envelops the formidable decision making process required to obtain, refine, blend, and distribute multiple products to a vast network of storage locations and consumers. The conclusion promotes the continuous sharing of information along the supply chain to best support the decision process at each step of production (Neiro and Pinto, 2004).

The Neiro-Pinto model includes elements of the processing unit reduced to a single refinery model, a tank model that mixes refined ingredients and stores final products, and a pipeline model that distributes these products throughout the supply chain, where profit is optimized. This approach is applicable to the current study, because it allows the consideration of specific nodes capable of processing middle distillates. The results indicate that coordinated strategies that consider planning and production throughout all stages of the process are necessary to maximize the productivity and profit of a petroleum supply chain (Neiro and Pinto, 2004). The formulation provides justification of conservation of flow applicability to refined petroleum products. Additionally, the network constraints must meet demand requirements in order to remain feasible. These concepts are reflective of common practice within the downstream petroleum industry.

Al-Qahtani and Elkamel (2008) develop a general petroleum network model. They described a transforming energy marketplace where refiners and producer remain competitive by considering a holistic network that can quickly respond to changing market conditions. They recommend a process that optimizes the network by minimizing production expenses and capitalizing on unutilized system potential. The authors recommend techniques that allow linearization of complex functions including materiel processing, product selection, capacities, and demand functions. The case study considers a multi-site refinery network using a variety of petroleum stock. The authors suggest that this model is efficient and applicable to all levels of planning during steady state operations in terms of stock costs and demand (Al-Qahtani and Elkamel, 2008). The simplification of the network to a linear model provides an example of how a military analyst might streamline their planning processes when confronted with limited time and data at the expense of result precision or accuracy.

In a follow on article, Al-Qahtani and Elkamel (2010) describe geographically diverse refinery networks entitled, "Robust planning of multisite refinery networks: Optimization under uncertainty." The authors propose a stochastic extension of the multisite refinery problem that considers variation in market conditions. A stochastic approach may be necessary to capture the random and often unpredictable nature of market effects. Al-Qahtani and Elkamel propose a two stage stochastic MILP that uses robust optimization in order to minimize annualized costs associated with the production network. The resulting model highlighted the volatility of the petroleum marketplace and recommended a robust optimization planning approach to account for the potential variations in market and supply effects. The authors present a familiar deterministic model of a network of refineries and apply the effects of these market uncertainties using a non-linear component to implement the robust optimization. The test model implements this robust optimization model using a three site refinery network to identify its sensitivity to changes in market and supply factors (Al-Qahtani and Elkamel, 2010).

This simulation aspect of their approach employs a Monte Carlo sampling system to assign appropriately generated values to probabilistic inputs. The model is tested against a single refinery and a network of refineries to determine what insights may be realized. The authors demonstrate that there is an improvement in model stability to variations in stock, product, and demand factors that affect profit that is scaled by the risk attitude of the investor (Al-Qahtani and Elkamel, 2010). In the event of a disruption, a similar stochastic technique allows the modeler to produce random variation in the duration of infrastructure outages or the effectiveness of strategic policy implementations such as an embargo.

An alternate approach involved sequential decision making strategies to maximize the returns of a downstream petroleum market. Mendez *et al.* (2006) explore a variation of mixed

integer linear programs that use a combination of optimization and short term scheduling theory in oil refinery operations. This proposed approach seeks to combine solutions of petroleum mix optimization with efficient scheduling in order to maximize industry economic success while consistently meeting demand (Mendez *et al.*, 2006). In a period of conflict, similar short term strategies may apply to sourcing the priority end users with acceptable petroleum products. This type of solution represents a potential decision process that an adversary could utilize in planning petroleum distribution during a situation where supply and demand constraints change more rapidly. An approximate dynamic approach would iterate updates to the model with changes in end user inventories and infrastructure availability over time progression.

Mendez *et al.* (2006) introduce an off-line blending problem that implements a proposed MILP. The methodology involves generation of initial product recipes at the refinery in consideration of non-linear processes. The approach determines whether the proposed product lines are within specification tolerances and informs a scheduling model that specifies the destination and volume of transportation shipments to meet the most profitable demand levels. The authors utilized three example problems based on various production schedules to determine the adequacy of the model in implementing the proposed solutions. The authors conclude that the convergence of sequential linear programs to produce a point solution was an effective formulation technique to solve this complex and multi-stage problem (Mendez *et al.*, 2006).

Ejikeme-Ugwu *et al.* (2011) describe an approach that focuses on the effects of market demand while limiting price variation or supply interruptions. The authors develop a refinery planning model where a two stage stochastic linear program develops an initial model and adds stochastic elements related to market parameters such as stock cost, supply availability,

planning factors, and prices. The authors utilize a method referred to as sample average approximation in order to generate an optimal solution in an environment that is sensitive to demand uncertainty. The model then implements a recourse process to improve the optimization resolution and results (Ejikeme, *et al.*, 2011). The advantage of this approach is its applicability to a network where demand varies widely based on perceived availability, collapsing infrastructure, illicit network outflows, and other realities that accompany a distribution network in a conflict zone.

As refinery networks compound with transportation hubs, pipelines, and other infrastructure, the size of the problem set becomes increasingly complex. This complexity can result in extensive requirements in solution time and computing power that require resolution. A heuristic approach to solving multi-pipeline programming is presented by Herran *et al.* (2012). The authors attempt to increase the model efficiency of a mixed integer linear programming methodology. The proposed method uses techniques for searching areas around a known solution using global search meta-heuristics. The authors identify the contribution of transportation costs to petroleum product price as a relevant matter because it allows refiners to realize the highest savings in operational costs. Refinery processes have very little variation once constituted and are not easily altered or streamlined without significant capital investment. Crude stock prices act as a neutral contributor to pump prices because refiners generally purchase feed stock from the global market at similar prices. Since refiners generally pay similar prices for crude stock, they are able to pass this cost uniformly to the customer (Herran *et al.*, 2012). This model explains why end user energy prices tend to adjust uniformly amongst competing vendors.

Additional solution techniques for problems with increasing complexity are presented by Gunnerud *et al.* (2010). The authors employ large scale optimization techniques utilizing the Dantzig-Wolfe decomposition in order to assess non-constant rate offshore oil production near Norway. The model constrains production factors such as transport capacities and raw material availability. These dynamic constraints often progress throughout the entire network and require a real-time solution that optimizes the network while accounting for these changing factors (Gunnerud *et al.*, 2010).

The authors recommend a real-time approach that decomposes a system of many decision variables and dynamic constraints to produce clusters that contain each commodity subsystem problem within the process. They apply linearization techniques to each cluster and initialize Dantzig-Wolfe decomposition to produce a parallel implementation of the master problem that produces a feasible solution in a fraction of the time required for competing approximations (Gunnerud, *et al.*, 2010).

A stochastic model that also utilizes large scale optimization is presented by Oliveira *et al.* (2014). The authors propose that many aspects of the supply chain including demand, stock costs of crude supplies, selling prices, and other highly variable factors are the primary drivers of petroleum network flow. These highly unpredictable indicators dominate the decision cycle for the production and distribution of refined products and require a two-stage stochastic program that applies supply chain optimization in order to achieve a reasonable solution (Oliveira *et al.*, 2014).

The authors propose a model that is formulated as a linear program and coupled with Benders' decomposition algorithm in order to build a master-sub problem involving two stages. The required Markov processes that account for the discussed unpredictability is applied to the

second stage of the problem. The authors then experiment with various deterministic and dynamic cuts in order to reduce the problem to a manageable size. Upon reaching an acceptable model, a heuristic approach is applied in order to limit the required iterations. The authors conclude that the approach successfully applies stochastic decomposition to a deterministic problem with a result that is less than a quarter the processing time of a full-space deterministic solution method (Oliveira *et al.*, 2014).

Network modeling techniques are sufficiently investigated in the body of research to allow specific application to middle distillate fuel production and distribution systems. Networks supported by middle distillate inputs can also utilize a similar framework. The complexity of the network will compound with the addition of cascading effects that measures changes in product input on dependent systems. Systems of transportation, agriculture, consumer use, and other industries link directly with the outputs of the petroleum network model under consideration in this study.

2.3 Network Interdiction

Network interdiction is a critical component of the problem focus of this study. Multiple researchers have considered the most effective way to interdict a network, and petroleum interdiction appears prominently throughout the literature. The most effective techniques are well documented, but this review focuses on applications to petroleum networks with potential to assess or limit the impacts on local and world economies. Much of the body of knowledge resulted from studies that investigated the protection of critical infrastructure networks from attacks or other contingency disruptions.

Wood (1993) provides an early example entitled, “Deterministic Network Interdiction” in an application that supported operations against the drug interdiction network in Latin

America. This approach utilized an interdicator model that minimized the maximum flow of illicit trade through disruption of network arcs (Wood 1993). This approach has since expanded into a number of different types of human, commodity, and information networks.

Israeli and Wood (2002) present an interdiction problem that models the interdicator and the network operator in a leader (attacker) and follower (defender) capacity. This process requires the operator to possess a capacity to repair or bypass disabled sections of the network. The attacker will therefore seek to increase the length of the shortest path to the maximum possible distance or time. The authors apply an approach based on Bender's decomposition in order to analyze the network impacts of leaders and followers of varying capacity, and they reinforce this process with a series of supporting theorems. The most applicable concept to this thesis is where the authors consider a situation of an arc that is destroyed by the interdicator. The associated covering algorithm provides a methodology for interdiction modeling of vulnerable arcs or edges within a network structure. This feature is relevant to a petroleum distribution pipeline if the structure or capacity of the system is vulnerable to disruption (Israeli and Wood, 2002).

Lim and Smith (2007) expand the interdiction problem to a multi-commodity flow network. Because refined petroleum mimics a commodity in almost all markets (Inkpen and Moffett, 2011: 479), this approach is applicable to this study. The authors specifically cite its utility in a network supply chain. The interdiction model implements a leader follower problem similar to what is proposed by Israeli and Wood (2002). The subsequent applications include discrete interdiction using completely destroyed arcs contrasted with a continuous approach that allows the interdicator to apply non-linear variation to a network arc (Lim and Smith, 2007).

Granata *et al.* (2013) describe an alternative interdiction model that disrupts connectivity by targeting the most vulnerable path called a critical disruption path. The authors propose a method to identify the critical disruption path within a network. They formulate their problem using a mixed-integer linear program and employ a branch and price algorithm. This process begins with a path formulation and simplifies the model by branching from a restricted relaxed master problem, which models decision variables continuously (Granata *et al.*, 2013). The authors implemented the solution in CPLEX and compared the results of the branch and price algorithm to analyze effectiveness.

Brown *et al.* (2006) present a study into the defense of infrastructure networks deemed critical to functioning public services. Although focused on terroristic threats to the United States or its allies, the premise of the article is highly applicable to the notion of cascading effects. The authors describe an attacker defender model that measures the importance and vulnerability of an asset while applying appropriate levels of interdiction or risk mitigation to minimize the overall system impact. A simplified linear model is used to represent crude petroleum network flow that serves as a basis for further analysis. This application limits the site specific complexity of a refinery optimization model while retaining the definition necessary for strategic considerations (Brown *et al.*, 2006).

Brown *et al.* (2006) use the strategic petroleum reserve in Louisiana, electric power grids, and supply chain management as case studies. In the case of the strategic reserve, the authors model the complete system of refineries, ports, and transportation infrastructure and apply a limited version of their attacker defender model. The study concluded that petroleum networks are highly fragile and vulnerable to attack compared to other infrastructure (Brown *et al.*, 2006).

Kennedy *et al.* (2011) describe the process of nodal interdiction as an alternative to research limiting disruption techniques to arcs and edges. This disruption is defined by disabling an infrastructure target to prevent its operation. The authors recommend an attacker-defender model that implements a maximum flow objective function, and measures the effectiveness of a nodal interdiction against the existing network. This approach allows the modeler to determine the maximum capacity of the network and determine the impacts of disruption. The formulation uses a bi-level maximum flow mixed integer linear program that disables the network at the nodal interdiction site. This concept is extended to a program that disrupts nodes and edges simultaneously (Kennedy, *et al.*, 2011). This framework provides useful insight into a network that operates under maximum flow conditions that might be present in the event of a petroleum network interdiction. Storage facilities and polyducts may both be vulnerable to disruption, although disabling a storage tank does not necessarily disrupt downstream network locations. However, both possibilities will impact fuel availability to end users that include military applications.

R -interdiction refers the nodes of a network that when interdicted, result in the greatest weighted distance between a demand node and a most convenient supply node. This concept informs models that attempt to optimally weaken a network using R number of planned interdictions at network facilities. Because military planners are generally provided a package of available sorties or strikes, the R -interdiction model provides a beneficial concept for simplifying and maximizing the assignment of these resources. Church *et al.* (2004) describe a model that iterates the number of strikes, R , and how these strikes might best impede a network by maximizing the effects of the strikes measured in terms of resulting shortest distances between nodes (Church *et al.*, 2004). This solution is highly applicable to petroleum supply

lines since the loss of a storage node can seriously debilitate the flow of commodities to dependent end users. In the case of refined petroleum, the shortest distance will translate to the greatest flow rate between nodes using the remaining arc capabilities.

Computer experimentation is an additional tool that is available to consider an interdiction decision space. Similar to R -interdiction, experimentation allows the development of courses of action to impede a petroleum distribution network. Depending on the options of disruption, computer experimentation on a network model would provide the user with detailed information on the decision space. Sacks *et al.* (1989) codified the use of statistical computer models to measure responses to multiple factor settings in a deterministic model. Similar factor settings could accompany interdiction decisions regarding vulnerable pipelines, storage facilities, or supply points within the refined petroleum network. The results of such an investigation can inform statistical analysis and response surface representation by investigating responses throughout the design space at a limited number of runs (Sacks *et al.*, 1989).

Johnson *et al.* (2010) demonstrate how high order polynomials can model input-output interactions that may require significant computational power to otherwise execute. The authors propose four types of space-filling designs for comparison. Space filling designs are methods used to efficiently represent a large number of factor settings within a design space. The space-filling designs that are investigated by the authors include uniform, maximum-entropy, Latin-hypercube, and sphere-packing designs (Johnson *et al.*, 2010). Space filling designs are intended to investigate as much of the decision space as is possible within constraints of time and computing power. However, an experiment with limited factors or discrete numbers of factor settings may allow investigation of the entire design space.

Multiple interdiction models are relevant to determining how to best disrupt a commodity network. Petroleum refineries are vast and complex operations whose locations and capacities are widely known. The transportation networks that support product delivery are similarly complex. Despite the dominance of pipeline systems, distribution may rely on any number of delivery methods including rail, barge, truck, or freighter. Available storage facilities may be highly diversified in size, location, and vulnerability (Inkpen and Moffett, 2011: 431). A first world military superpower such as the United States possesses the capabilities to effectively disrupt these networks. However, complete disruption may not be achievable. Improperly implemented network interdiction could result in undesirable cascading effects causing suffering throughout the regional economies with little measureable results in reducing the capabilities of an adversary. The ability to measure the first order effects of interdiction is essential to assessing the cascading second and third order impacts on the affected economies.

2.4 First Order Impacts of Disruption

Empirical analysis provides a tool to predict the price fluctuations of commodities. This technique is evident in the analysis of the significant refinery interruptions that occurred after Hurricane Katrina. The use of empirical modeling enables the assessment of how market shocks and network distributions might impact highly sensitive market conditions such as the price of refined petroleum products.

Kendix and Walls (2010) describe the use of regression analysis of petroleum industry indicators. The details of the research include references to the US Department of Energy's Information Administration where available data is compiled for almost every necessary aspect of domestic energy markets. This data includes refinery capacity, storage networks,

distribution, usage, prices, and a litany of other useful data. The author did indicate that this data is not available for individual refineries from the Department of Energy, but suggested a methodology to disaggregate these data sets and determine a relationship between individual refineries and the fuel markets that they support. The author further identified refinery outages identified in the United States and linked these events with the time, date, location, duration, and offline capacity in addition to the type of refinery capacity that went off line (Kendix and Walls, 2010).

Kendix and Walls also point out a major concern with the use of empirical time-series data that is present in almost any data set that regresses against price. These time series data points introduce inherent dependence between data points that is not easily mitigated in the regression analysis (Kendix and Walls, 2010).

Fink *et al.* (2010) present a risk-based approach that gauges the overall impact on market prices caused by a weather disruption. They consider the forecasting of tropical storms over two decades to examine whether the prices are linked to a weather forecasting horizon. The authors sourced forecasting data from the National Oceanic and Atmospheric Association (Fink *et al.*, 2010).

The term ‘crack spread’ refers to the difference between the cost of crude petroleum to a refiner and the expected price of the products; it is used to define the industry profit margin. This calculation usually compares the price of two units of gasoline and one unit of diesel to the cost of three units of crude stock (Inkpen and Moffett, 2011: 459:460). Fink *et al.* utilize a ‘crack spread’ calculated from the observed changes in the prices of refined products contrasted with the stock prices of the required crude petroleum as a response variable. The data is concentrated around the third refinery district of the United States known as Petroleum

Administration for Defense (PADD III) that includes all Gulf Coast states and their refineries (Fink *et al.*, 2010).

Changes in forecasts and the associated variations in crack spread statistics allow analysts to track how the expected landfall location and magnitude of the storm will influence domestic prices and refiner profits. Because such a disproportionate amount of the refinery capacity of the United States is located within the path of the Atlantic Hurricane corridor, the tools utilized provided some robust analysis due to the high number of data points. The crack spread statistic led the authors to conclude that the changes in the 24 hour forecasting of tropical storms would significantly influence the trading price of various petroleum commodities (Fink *et al.*, 2010). This conclusion is applicable in any scenario that includes a predictable disruption to the refined petroleum network and a reasonable extension to an expected armed conflict could result in similar forecasting effects on global prices.

Choi and Hammoudeh (2009) investigate the problem of time series data in price modeling of commodities including crude oil and its refined derivatives. They seek to identify the occurrence of long memory within the petroleum industry using crude spot price data collected over two decades. The identification of associated autocorrelation within the data that falls between parameters associated with long memory patterns is determined by analysis of price returns from the data set (Choi and Hammoudeh, 2009).

The authors use the presence of long memory to populate an estimate and run multiple forecasting models that predict future data within a 20 day output. The model implements the effects of price variations and estimates the length of the market effects with significant accuracy in crude and most of its products. The results indicate that even a significant break associated with conflict or economic disaster will not affect the data substantially to cause

variations from the long memory model of petroleum price for the cases examined (Choi and Hammoudeh, 2009).

Jason and Kristin Fink (2013) further explore the effects of forecasting on the prices of oil and gas. The study focuses on the belt of refineries on the US coast of the Gulf of Mexico and determines that the price fluctuations have actually reacted earlier over the course of a decade from a 24 hour horizon reaction to one of 48 hours. Reasons for this increase include the development and refinement of forecasting models that allows a much greater ability to estimate impacts on the industry. The authors collected similar data to Choi and Hammoudeh (2009) with an expansion into the most recent decade of occurrences. They developed a risk assessment methodology and applied an equity return regression model that sources the data points presented. Reintroducing the notion of ‘crack spread,’ the authors are able to identify the conditions where events related to a hurricane and associated forecasting will result in notable changes to the prices of refined petroleum products. Additionally, the authors identify that the robustness of the capacities available to larger refiners allows them to use remote infrastructure to react to short markets caused by hurricane disruptions and capitalize on the temporary price fluctuations. The conclusion reiterates that the model of forecast horizons and attributed price fluctuations has moved in a direction that increases prices and profits for traders and refiners (Fink and Fink, 2013).

Blair and Rezek (2008) describes the effects of catastrophic hurricanes in the refinery region of the US Gulf Coast on various market indicators. Most notably, Blair and Rezek use an error-correction model to determine how quickly the measurable supply effects pass through the system to affect prices to the consumer. An empirical model implements error-correction terms that uses a long run adjustment parameter to determine how quickly price changes occur and

estimates the timeline of the system's return to steady state. Blair's model indicates that this pass through is extremely quick; there is not significant evidence of market flaws that affect the price pass through from crude stocks to spot prices of gasoline during the Katrina hurricane event (Blair and Rezek, 2008).

Kaiser's (2008) article entitled, "The impact of extreme weather on offshore production in the Gulf of Mexico," explores the consequences of tropical storms and hurricanes on the oil industry in the Gulf Coast with a focus on shut-in production using an empirical model based on historic production coupled with weather events. The author coupled this information with production statistics from the Gulf of Mexico. Kaiser's summary of the capacity of the region highlights the complexity of mathematical analysis of the complex distribution and production system (Kaiser, 2008).

Kaiser describes the shut down procedures that are explored in the model and the timeframes for shut down, evacuation, and restoration of capacity. The formulated model uses seasonal impacts, cumulative impacts, and event impacts to build associated empirical models detailing the effects of shut-in production at multiple facilities along the Gulf Coast. The author concludes that the impact on shut-in production is present does not delineate the magnitude (Kaiser, 2008). In the case of Katrina, the shut-in procedures occurred with sufficient advanced notice to allow the refiners to conduct a safe shut down procedures. In the event of armed conflict, there may not be sufficient time to allow proper system shut down, which will exacerbate the impacts and associated cascading effects.

Kaiser and Pulsipher's (2006) publication is entitled, "Modeling the cost of shut-in production and the value of information in the Gulf of Mexico." The work describes weather delay risks in the Gulf Coast petroleum markets. He proposes a methodological framework that

will provide a cost estimate related to previously discussed shut-in procedures. The author provides gradient charts that detail the risk involved with severe weather impact in all locations within the Gulf of Mexico, many of which contain production or refinement capacity (Kaiser and Pulsipher, 2006).

Kaiser and Pulsipher (2006) present production recovery and delayed recovery models that vary based on the number of events and the number of recovery sequences. These parameters are augmented with a cost adjustment for petroleum and gas using a function of the discount rate and price over the duration of the shut-down. The empirical model uses a present value function that estimates the loss of cash flow during a production shut-in. This model is intended for a corporate entity that might attempt to forecast economic losses based on a contingency event such as a hurricane. Kaiser and Pulsipher (2006) conclude that the information is provided by such a model will support the decision cycle that determines the economic risk of shutdown in addition to other factors of safety and necessity when considering the proper mitigation strategies for an approaching weather event (Kaiser and Pulsipher, 2006). This type of data is an important input for the determination of what procedures would allow production to resume the most efficiently.

The body of research involving refinery disruptions heavily sources empirical evidence to determine the expected primary effects on price and global markets. This information is highly valuable in determining market impacts that result from varying degrees of disruption to a petroleum network. Most essentially, the data sources identified by previous research allows for estimation of anticipated downtime for a refinery shutdown. This estimation can use empirical data or create stochastic function using known parameters. While a hurricane is slightly more predictable than the effects of intentional state inflicted network interdiction,

there are parallels between the effects on a refinery network and the associated economic instability. Since empirical evidence and data is available from most of the world's petroleum markets, this information will inform an appropriate model to predict the immediate impact to refined petroleum supply, refinery outages, and product price variations.

2.5 Cascading Effects of Disruption

Once the immediate impacts of a disruption occur, the impacts of price fluctuations and shortages will begin to reverberate across the infrastructure system. Petroleum provides an inexpensive and available form of energy in almost every economy in the world. Within the middle distillate products that are the focus of this study, there is vast potential for extensive cascading impacts to affect nearly every corner of a society. The events of September 11, 2001 resulted in a renewed focus on infrastructure protection. A significant byproduct of this research resulted from the analysis of interdependencies in public infrastructure networks. These networks support each other in many essential ways.

The existence of these interdependencies was highlighted by Rinaldi, Peerenboom, and Kelly (2001) in a study of the subject of critical infrastructure as part of the US National Security apparatus. The authors cite a litany of disruptions including telecommunications satellite failure and electricity generation shortages. As the effects of these failures cascaded to other industries, the authors noted the appearance of four types of interdependent systems. Physical interdependencies involve systems with direct inputs and outputs to one another where the functionality of one network requires inputs from a source network. Cyber interdependencies occur when automation systems control the execution of multiple physical networks and result in a vulnerability to informational disruptions. Geographic interdependencies exist in systems that have significant collocation between the arcs of

different networks such as with telephone and power lines. Human decision making schemes may result in logical dependencies that link various networks through responses to dynamically interacting systems (Rinaldi *et al.*, 2001).

The first order effect involving disruption of oil pipelines appears within the interdependent model and shows second order effects upon refineries and storage nodes. The disruption manifests itself in excess inventory at refinery locations and associated depletion at storage facilities. These physical impacts will cause supply shortages through road and air transportation networks. These are typical cascading results that the authors classify as linear or complex depending on the predictability of the outcome. Further classification suggests that the level of correlation between networks will determine the degree of the impact on associated systems (Rinaldi *et al.*, 2001). Their article presented an important definitional framework that informed extensive follow-on exploration of the linkages between industries and their associated infrastructure networks.

Alcantara and Padilla (2003) considered the potential impact of disruptions to energy markets as a result of reducing greenhouse gas emissions in the Spanish regulatory structure. The proposed methodology investigates the vulnerability of key economic sectors to regulatory reductions in energy consumption using a Leontief model. The model proposes linking the demands of an industry and criticality of the demand to industry production to define the elasticity of industry production to increasing energy demands. The results highlighted agriculture, energy production, steel production, transportation equipment, and chemicals as key sectors of potential impact (Alcantara and Padilla, 2003).

Rinaldi (2004) expanded the discussion of critical infrastructure by recommending a modeling and simulation approach to investigating interdependency. He highlights the national

security requirement for determining the various critical network vulnerabilities to terror attack and cyber attacks among other goals. Rinaldi presents modeling approaches involving supply chain systems that apply directly to the oil and gas industry. He also recommends the use of dynamic simulation to determine the downstream impacts of network interdiction. Agent-based and physics-based models appear as alternatives to investigate physical infrastructure models. The introduction of Leontief models appears in this article and its definition is essential to further research in this area. Leontief Input-Output models estimate economic flows in a linear and time dependent system that accounts for the production, transportation, and distribution of commodities. Rinaldi describes the applicability of these models to an interconnected network of public infrastructure (Rinaldi, 2004).

Zimmerman (2004) presents an investigation of incidents that resulted in observable cascading failures as a result of interdependencies that exist in public infrastructure. The author iterated the difference between spatial interdependency that relies on co-location of networks and functional interdependencies that result from a system requiring direct inputs from another in order to remain functional. A resulting database demonstrated interconnectivity in a variety of industries including oil and gas pipelines and many networks that they support. Oil pipeline disruption did not appear as a common observation, but the interruption of gas pipelines resulted in 19 documented cases of failure in an adjoining industry (Zimmerman, 2004).

Peterson *et al.* (2006) survey applications to the examination of key infrastructure interactions. He highlighted the occurrence of interaction for reasons of geospatial proximity, direct input reliance, and linkages that result from operational strategies of various organizations. Effects are categorized in terms of PMESII, which the author defines as the interconnected political, military, economic, infrastructure, and informational systems of a

society. The author identified three specific systems that are relevant to the study of petroleum pipeline infrastructure. These models include Athena, CIP/DSS (Critical Infrastructure Protection Decision Support System), and an Australian government model called CIPMA. Petersen's research revealed a significant level of governmental and industrial participation into the study of second and third order effects caused by system interdependencies. Contributing US Agencies summarized in the study included the Argonne, Oak Ridge and Los Alamos National Laboratories as well as Air Force Materiel Command (Peterson *et al.*, 2006).

Haimes and Jiang (2001) develop an interoperability model based on the work of Leontief that explores the level of dependency between interconnected networks. Santos (2006) expanded the concept to interconnectivity in economic systems such as finance, service, and commodity flow utilizing a similar Input-Output model. A terrorist attack is used as a premise for the economic disruption. The resulting model demonstrates oil extraction and refinement as two of the top sectors that contain interoperability with other industries. This data is utilized to produce an estimate of overall economic loss to the US economy based on a potential disruption. Again, petroleum refinement appears as a significant contributor to economic loss (Santos, 2006).

Setola *et al.* (2009) also applied the Input-Output model to critical infrastructure dependency in an analysis of Italian public utility systems. The approach utilizes an Input Output Interoperability Model (IIM) to assess the impact of one industry on the function of another. The approach measures how an industry plays a role in the operations of another industry using a dependency index. These indices are a row summation of a Leontief Coefficient that describes the compounding effects caused by significant interdependency. The Leontief Coefficient is calculated by dividing the input of a product in a specific industry by the

total outlay of that product output. The measurement determines the relative level of dependence of an industry on a particular type of input or product. The resulting Leontief model follows interactions where cascading effects of one industry could result in the collapse of another dependent industry. The methodology includes analysis of higher order dependencies where an industry is impacted indirectly through cascading effects using a relative increment that measures the transmission of impacts along a series of dependent facilities. The authors analyze expert opinions to determine the impacts and consequences of infrastructure degradation. The article defines fuzzy numbers as entities that account for unknown factors that are collected from subject matter expert data. They implement fuzzy numbers to analyze subjective information from experts (Setola *et al.*, 2009).

Lee *et al.* (2007) discuss a network flow model of interconnectivity that represents an interdependent layer network. This approach appears as a mixed integer program that minimizes implementation cost while considering the impact of shifting commodity availabilities. The model extends arc-node structures of interdependent supply and demand relationships between infrastructure networks. Electric power, communication, and transportation system interoperability in Lower Manhattan appear in the scenario implementation of the model. The iterative process used to define constraints and variables is versatile and could provide the basis for a study of petroleum network disruption and its cascading effects (Lee *et al.*, 2007).

The Lee model adds the critical component of demand shortfalls that are described as a slack variable within the solution set. The weighted slack of demand nodes describes the consequence of a network disruption manifesting in unmet demand. This shortfall will determine the degree that a dependent network is affected and highlight the priority for

restoration efforts (Lee *et al.*, 2007). The concept of weighted slack contributes an essential component to predicting cascading effects. Within the context of a petroleum supply network, this slack may represent the amount of end user demand that is unfulfilled at each distribution node. A decision variable representing unmet demand allows the consideration of the impact of unmet demand upon the larger economy or civil infrastructure. This concept will contribute to the analysis of interdependency by predicting the level of unmet demand caused by network interdiction.

Nieuwenhuijs *et al.* (2008) authored a research paper entitled, “Modeling Dependencies in Critical Infrastructures.” The authors seek an understanding of critical infrastructure dependencies and propose a model to represent their relative significance. The methodology measures the impact or effects of dependency by specific quality of the delivered commodity including volume of food or petroleum, speed of transportation, temperature of heating water, pressure of gas or water, voltage of electricity, and so forth. The model delineates the response of the supported entity by the adjusted functionality level that results from the loss in associated dependent supply during a deterioration period and recovery stage. A time response measures the impact of the loss in commodity over a specific time period related to the functionality of the supported system. The model output describes states of operation including normal, stressed, crisis, and recovery based upon the services and products available. The authors capture the level of infrastructure movement through various states that are determined by the response caused from lack of a required commodity (Nieuwenhuijs *et al.*, 2008).

Interdependency results from links between networks that result in a physical or dependent connection between their functionality. The degree of this interdependency is determined by the degree to which these links interact with the overall network. Fu *et al.*

(2014) developed an investigation into cascading failure of interdependent systems. The degree that this dependency exists is calculated by the ratio of dependent nodes between two networks. Additionally, the redundancy of these networks is calculated by the amount of supply nodes that a dependent node in an adjacent network might enjoy (Fu *et al.*, 2014). In the context of the problem statement, a highly redundant transportation network might enjoy several potential sources of diesel distribution from the petroleum supply network. A high degree of dependency would also exist in a transportation network since a preponderance of nodes required input from a petroleum distribution network. The impact of this interdependency is evident in the aggregate performance resulting from a network disruption, which is calculated using the size of the disruption.

Barker and Santos (2009) describe the essential role of inventory in the mitigation of supply chain disruptions. A robust supply chain with significant inventory can withstand a disruption in production or delivery of goods. Higher levels of inventory, while expensive, can increase the resilience of a distribution network that distributes products supporting critical infrastructure. The impacts of various levels of inventory manifests through time and is represented in an input-output model (Barker and Santos, 2009). Similarly, the storage capacities of petroleum networks allow a network manager the flexibility to respond to various types of supply disruption. Larger quantities of inventory that are dispersed throughout a network will provide a time buffer that acts to mitigate the impacts of interdiction.

Other applications of the critical infrastructure interdependency models include Johansson and Hassel (2010), who provided a case study oriented on a railway. Zhang and Peeta (2011) provided a study that captures techniques for mapping connectivity between

physical infrastructures and documents the use of various applications in transportation and energy system interdependency.

2.6 Construction of a Generic Petroleum Network Model

The petroleum network distribution system comprises of three elements required for efficient downstream operations. The refinement and distribution of middle distillates requires a refinery network with local storage, regional storage depot locations, and distribution nodes available to all varieties of consumers. Each of these nodes must access reliable transportation that can take the form of pipelines, waterborne vessels, truck transportation, and railways. (Neiro and Pinto, 2004). The specific medium utilized to transport finished middle distillate products is specific to each local economy. Pipelines are essential to liquid fuel distribution in the continental United States. However, specific economies may also rely on alternative shipment methods as their geography and economic conditions allow.

Refinery operations must receive raw materials in the form of crude production so long as the supply chain remains operational. Each refinery hub must have sufficient storage capacity for each type of crude required to generate their desired output in line with projected market demand. In fact, the role of storage is an essential element to any refinery network and distribution model, including the middle distillates necessary for military operations. Refineries require storage capacities available for blending and storage of finished products in addition to holding tanks for crude stocks. Each of these storage nodes has a very specific minimum and maximum capacity that requires constant scheduling strategies in order to maintain sufficient capacity (Pinto *et al.*, 2000). Once derived, petroleum products require sufficient shipment capacities to reach their initial destination in a timely manner. The distribution hub that receives the shipments must also meet capacity constraints defined by their minimum and

maximum storage capabilities. Schedulers must also balance this process with the availability and capacity of a variety of shipping methods. While pipelines are the primary means in many highly developed distribution networks, trucks, rail, and barge delivery systems are also capable of distributing refined products. These alternative methods may allow a network manager to bypass disruptions in a pipeline based infrastructure.

2.6.1 Refinement Capacities

The design and capabilities of a refinery determine its ability generate finished products that meet market demand. Various blends of processed crude are mixed as intermediate distillates within a diesel pool storage unit to form a finished product that meets the specifications of the expected user. The crude stock, operating variables, and demand specifications are different for each refinery location. In the case of diesel and other middle distillates, this can occur through five common processes.

Crude distillation is the initial process for diesel production and results in the production of naphtha, kerosene, light and heavy diesels. Almost all crude stock undergoes atmospheric distillation, which involves the heating of desalted petroleum beyond its boiling point at local pressure. This process renders most of the crude into fractions that are collected in the order of their volatility for gases or density for particles that remain liquid (Inkpen and Moffett, 2011: 446). Although intermediate diesel products require blending or further refinement before completion, they could also begin the blending process immediately after atmospheric distillation (Moro *et al.*, 1998). From a standpoint of interdiction, the atmospheric distillation process ensures that military grade distillates are inextricably linked from lighter products used in many industrial and civilian applications. The disruption of distillation processes is a

decision or event that may contribute to cascading impacts and warrants investigation by the modeler.

Vacuum distillation is a follow on process that can extract gasoil from residue of atmospheric distillation and contribute to the diesel pool through other follow on processes. Intermediate products from vacuum distillation may undergo fluid catalytic cracking to produce light cycle oil. Residue from vacuum distillation may also enter a coking unit to become coking gasoil. Both coking gasoil and light cycle oil must undergo hydro treating before entering the diesel pool (Moro *et al.*, 1998). The process is summarized in Figure 1.

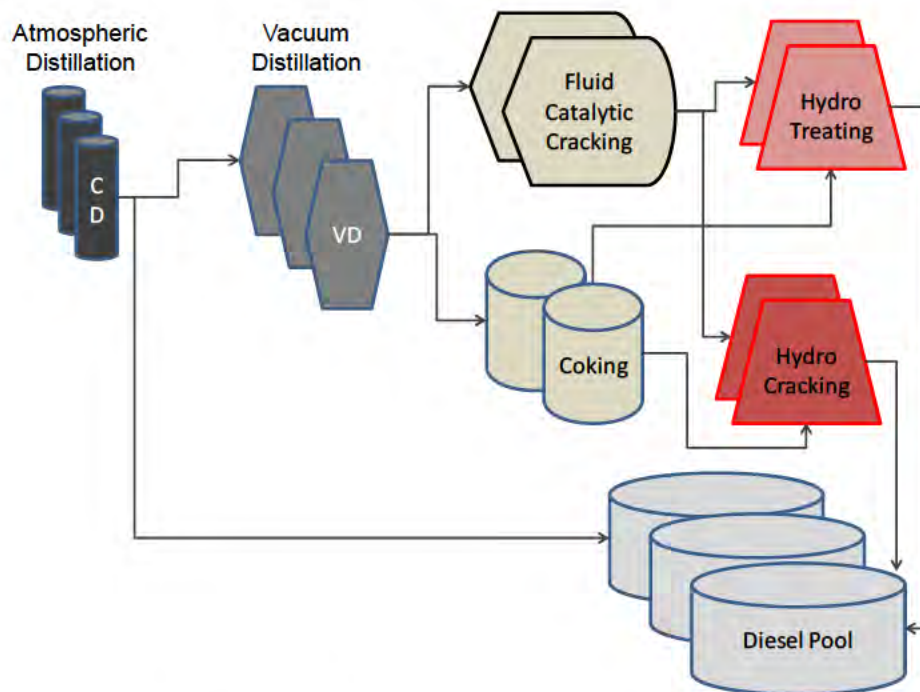


Figure 1: Middle Distillate Refinement Processes

Advanced refineries can also implement hydrocracking in order to achieve increased diesel outputs from less profitable residues. Hydrocracking uses the intermediate products of fluid catalytic cracking and vacuum distillation to render products that are sufficient to enter the diesel pool (Inkpen and Moffett, 2011: 446-448).

This refinement processes is highly non-linear. In addition, its implementation and results often remain known only to the operators and decision makers within the refinery complex. The non-linearity is compounded by the necessity of altering operations and production run settings to accommodate changes in crude stock and demand expectations. Modeling the interactions of these processes is limited by the availability of data from refiners as well as the inability to appropriately adjust an existing model to dynamic circumstances (Beyeler *et al.*, 2012). Because estimations of refinery capacities at global locations are readily available, refinery models are represented by approximations based upon the maximum obtainable output for critical types of middle distillates.

For the purposes of contingency modeling, planners might consider estimation of the contribution provided to the diesel pool by each internal refinement process. However, this type of estimate requires intimate knowledge of the facility in question, as well as knowledge of the decision cycle for military and political processes. In addition, such estimates require expertise regarding methods of disrupting specific product supplies without completely destroying refinery capabilities and inflicting undesired cascading impacts.

2.6.2 Importation

Economies that cannot refine sufficient petroleum product to meet local demand are able to utilize transnational pipelines and seaborne freighters to deliver their requirements. These products require a port of entry and are processed through the common distribution network for derivatives that are refined domestically (Inkpen and Moffett, 2011:431). The importation of refined petroleum is a significant vulnerability to many economies and presents a potential target for embargo or interdiction as described in the Background Section (1.1).

2.6.3 Storage Nodes

The network manager will impose constraints on the network similar to the marketplace constraints existing without the uncertainty of disruption. The storage capacity of demand points, distribution nodes, storage hubs, and production centers dominates the binding constraints. Sufficient storage capacity must be available at the intended destination in order to complete a shipment. Storage tanks that are at capacity or incapacitated by a disruption cannot accept shipments. This is particularly true of pipelines, where queuing of deliveries is not usually possible because they must maintain a minimum flow rate. Additionally, pipelines can only operate at the flow rate that meets the restrictions of the receiving storage terminal. This requires the pipeline to slow its shipment speed whenever the product flow is entering a storage terminal to ensure that it does not violate the receiving capacity of that location (Trench, 2001: 16). Many other forms of shipment can queue upon arrival at a delivery node. Most notably, trains, trucks, and waterborne vessels can provide temporary holding of their shipments until storage capacity is available, although this action reduces the capacity of the shipping arc during the queuing process. These types of alternatives are historically vulnerable to interdiction as evident in the Allied Transportation Plan described in Chapter 1.1 Background.

Fuel storage is an essential industry in any country with a refining capacity. Petroleum and its derivatives are a key component of commodities trading; the ability to receive and store shipments of liquid energy is essential to the functioning of the refinery industry on both global and regional levels. Speculators with the capacity to obtain and store refined commodities can counter the effects of an oil shock such as a distribution network interdiction. These speculators may include NOCs with refinement and storage capacity. In steady state operations, the managing agency of the storage node will determine how to optimally profit

from stored energy as market demand and prices fluctuate normally. In the event of an anticipated network interdiction, these agencies can counter the impacts of shortages by injecting stored resources into local markets using storage nodes that are positioned to bypass any interdiction (Unalimis *et al.*, 2012). Demand will ultimately deplete this storage capacity until the point of disruption is either bypassed or restored.

While storage nodes do have the capacity to act as transshipment nodes, this is unlikely during steady state operations. Storage nodes receive shipments from a pipeline for each type of product demand. There is very limited ability to inject products back into the pipeline from the supply node because the supply sequencing is set by the initial shipment point. Ultimately, the resulting effect on the network is that a supply node generally ships specific product packages to each demand point along a pipeline network. The shipment will bypass intermediate demand nodes and progress directly to the intended demand point as long as the shipper has positive control over the network operations (Herran *et al.*, 2010). In the event of a supply disruption, the storage node may be able to utilize the pipeline to ship to other demand and storage points along the network, assuming they retain functionality of their pumping systems.

Storage has an essential role due to its ability to mitigate network disruptions and its impact on the constraints of the delivery network of refined petroleum. Liquid products require storage volume, which necessitates an extensive infrastructure of holding facilities for any fuel network. These facilities represent a significant asset to an adversary who might utilize this capacity to offset the effects of an interdiction or any general market related shock to prices (Unalimis *et al.* 2012). Storage nodes are equally vulnerable because of their fixed location and

necessity in the supply chain. The consideration of storage capacity is a critical component of the problem methodology.

The modeler may not have access to detailed data regarding local storage capacities. However, storage capacity can be estimated as a multiple of the daily demand requirements based on the distance from the nearest supply location as shown in equation (2). Demand points that receive and store refined products require a substantial storage capacity and pumping infrastructure in order to operate. Supply network designers consider several factors in order to determine the appropriate tank size and configuration at each location. The tanks must contain enough storage space to satisfy demand based withdrawals while accommodating each required product separately (Miesner and Leffler 2006, 289-290). Miesner and Leffler (2006) recommend equation (2) in order to determine the appropriate size of a storage facility contained within a distribution hub. This formulation is used to estimate the tank size within the model required for the storage capacity in equation (6). Other methods to estimate storage capacity could use sales receipts, satellite imagery coupled with geometrical analysis, or available plans and as-built engineering specifications obtained from the network owner, subcontractor, or affiliate (Miesner and Leffler 2006, 289-290).

$$\begin{aligned} \text{Tank size} = & (\text{Average Demand} * \text{Cycle Time}) + \text{Safety Stock} + \\ & \text{Tank Bottoms} + \text{Safe Fill Allowance} \end{aligned} \quad (2)$$

Within this formula, cycle time represents the lapse between deliveries of each product. Safety stock provides a buffer that allows planning latitude between arrivals of stock. Tank bottoms represent the physical lower bound of tank capacity described by Pinto *et al.* (2000). Safe fill allowance is similar to safety stock in that it provides a buffer that prevents exceeding

the capacity of the tank during a delivery (Miesner and Leffler 2006, 290-291). Refined product distribution points utilize above ground tanks and represent a high value interdiction target. The loss of this infrastructure prevents distribution points from receiving or distributing products delivered by the polyduct.

2.6.4 Pipeline Arcs

The pipeline is the most effective method of transporting refined petroleum at a mass scale over significant interregional distances. Trucking lacks the volume and efficiency requirements that would allow it to viably replace a major pipeline in most economies. Rail traffic can accommodate significant interregional movement of refined petroleum products, but very few locations in the world have significant rail infrastructure to maintain product flow that is comparable to a major pipeline (Trench, 2001: 2-3). Waterborne vessels cannot reliably deliver petroleum reasonably close to adversarial military capacities unless the network user enjoys and maintains enormous geographical advantages that include unimpeded access to a seaport. The ability to credibly defend such facilities from air or naval attack is also necessary. A fuel delivery network might employ every available option in order to ensure that customers are receiving sufficient supply. This is particularly true of an adversarial power that is bolstering its network delivery options during or in anticipation of a network interdiction. However, there may not be a viable alternative to a major pipeline or waterborne route with significant flow rate capacities in even the most robust distribution network. A possible scenario available to the network manager is to employ available waterborne, road and rail assets to meet the most critical demand streams such as defense, power generation, and essential utilities and services. The volume available for shipment is dependent on the

availability of alternative shipping means under these circumstances. These alternative means are also subject to disruption.

A polyduct system is an extremely complex shipping procedure that routes multiple types of petroleum products through a single arc. Substantial arc capacity is required in order to implement this type of system. Polyducts are usually routed in a single direction since they connect the supply point directly with the demand or storage location (Herran *et al.*, 2010). Reversing this process requires a complete stoppage of flow in its primary direction and presents a highly complex planning challenge. Additionally, most polyduct networks connect the supply source directly with the demand locations and a reversal is not logistically necessary. For research scenario purposes, the modeler might assume that the network manager would commit available resources to restoring capacity rather than reversing flow direction.

In the event of inland pipeline disruptions, the most effective method of regaining capacity is to invest resources in a bypass or temporary patch of an interdiction point. PEMEX, the national oil company in Mexico, has demonstrated the capability of temporary pipelines as the only viable method of replacing the capacity after a recent natural disaster. Hurricane Ingrid destroyed the vital oil and product pipelines that supported Mexico City supply and refinery operations in 2013. PEMEX implemented a solution of temporary lines that met demand after an installation period of only four days. Reconstruction of this pipeline would have required several months while alternative transportation methods proved either unaffordable or infeasible due to capacity constraints (“Two Critical Pipelines Down and Millions of Dollars on the Line, PEMEX looks to Flexsteel,” 2013).

2.6.4 Generic Distribution Network

The resulting distribution network includes the refinement processes, importation of supplemental supplies, pooling of various product types, distribution through polyduct networks, delivery to storage facilities, and delivery to end users. This process is represented in Figure 2. The components of this network are essential elements for inclusion in an interdiction model. Notably exclusive to the refined petroleum market are the polyducts, refineries, and distribution storage nodes. Interdiction of rail, water, or surface transportation would inherently impact many other industries and infrastructure systems.

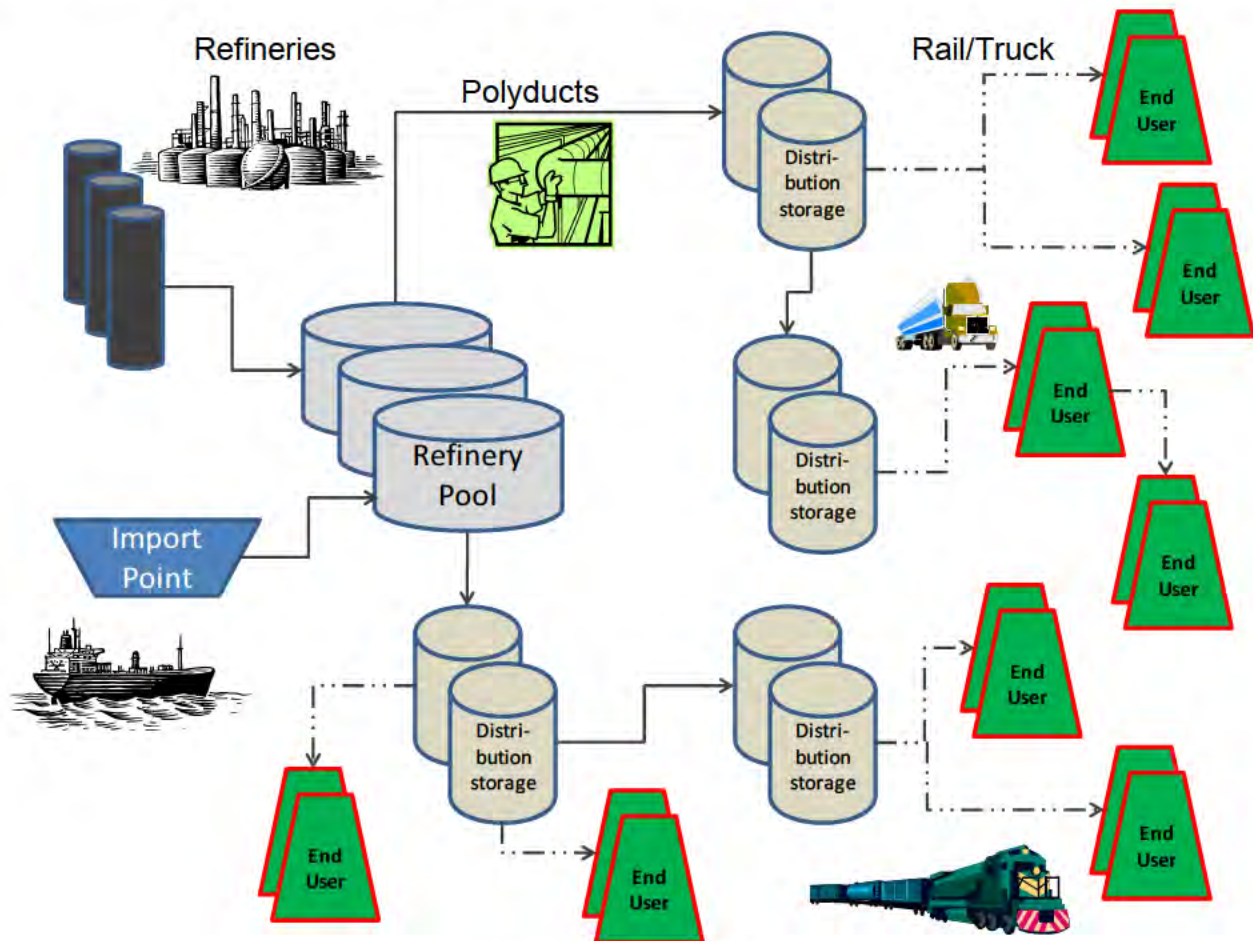


Figure 2: Generic Distribution Network

2.7 Aggregate Planning

In order to improve the versatility of the network, the refiner can disperse products as widely as possible based on available storage. A possible strategy that the network manager can employ is to maximize dispersal of their products using existing storage and shipment infrastructure. The manager possesses much of the logistical capacity to execute a strategy that ensures a robust network by prioritizing storage nodes based on their criticality and vulnerability to network interdiction. This strategy would occur using the same apparatus available to react to natural market fluctuations in supply and demand (Trench, 2001: 7). Rather than responding to price fluctuations that drive profit, the manager would respond to demand shortfalls based on the most critical needs as determined by a political or military apparatus. Since the most critical nodes are the priority for available supplies during a disruption in the distribution network, these storage hubs will be the first to increase their supply stockpiles. This strategy is implemented through Aggregate Planning.

Aggregate planning processes allow for a network manager to focus on a larger strategic objective when determining how to appropriate resources or distribute products across a wide range of customers. Aggregation involves the consolidation of planning considerations involving market conditions and capacities. A properly executed aggregate model allows management flexibility to meet customer requirements within the constraints of available capacity (Stevenson, 2012: 475). Developing an aggregate plan involves matching the known customer demand requirements with the capacity of a distribution system. Within the context of the refined petroleum distribution model, network managers consolidate all user demand throughout the system based on a series of distribution points. Each distribution point services a wide variety of customers for each refined product capacity.

Within the aggregate model, the manager considers their capacity to produce and distribute a resource to meet a set demand over the duration of an appropriate planning period. In an aggregate planning, demand is generally modeled as a known constant. Alternatively, the modeler can introduce a stochastic component that accounts for variations. The manager's purpose for utilizing aggregate planning models is to ensure that demand is efficiently met despite the occurrence of disruptions to supply parameters. This approach can address multiple types of issues, including bottleneck problems within a network (Nahmias, 2001: 117). Bottleneck problems such as a disruption in production, distribution network, or inventory storage capacity manifest in the event of a network interdiction. The implementation of aggregate planning allows the network manager to mitigate anticipated or unplanned disruptions by maximizing the utility of production capacity, supply distribution, and storage facilities.

Aggregate units are determined by the type of material or item that is produced. The most relevant unit to a petroleum supply chain utilizes volume of barrels per day (BBPD), often in multiples of hundreds or thousands. Aggregation must also match the appropriate context that adequately informs the model results (Nahmias, 2001: 116). Because each type of petroleum product sources a vast range of dependent industries, the petroleum distribution model will maintain differentiation of product type within the supply chain.

The ability to deliver goods to market is critical in any industry. Uncertainty over the capacities of a supply chain influences managerial decisions for a network. In the Basic Economic Order Quantity model, the producer receives an order of exactly Q units from a demand node. The producer ships this order to arrive exactly when inventories are depleted at the inventory location in order to meet expected demand. There is no lead time required in this

model, and orders are designed to meet demand while limiting inventory and storage costs (Stevenson, 2012: 566). This model utilizes Q as a constant for demand that does not vary over time. The significance of the variable Q is to indicate the amount that is shipped to a destination during the time horizon of an aggregated planning model.

The basic transportation problem determines how a product is profitably moved from its supply point to a distribution node near the end user. While the proposed methodology is focused on disruption of the maximum flow, elements of the transportation problem still exist. These elements include the supply points, transshipment nodes, demand requirements, and conservation of flow. Distribution Resource Planning utilizes the components of a transportation problem to inform decisions regarding the production and shipment of resources. This process allows consideration of alterations to demand (Nahmias, 2001:315-322). While local demand may remain fixed as described in Aggregate Planning, physical system demand is highly susceptible to disruption. The loss of storage pipeline, or importation capacities will alter the production requirements for refineries regardless of local demand variation. Distribution resource planning enables the consideration of physical demand fluctuations in the system that are proximate to network debilitation rather than demands of the end user.

Nam and Logendran (1992) provided a review of studies investigating Aggregate Planning Production (APP). They identified research regarding APP using methodologies that include Linear programming, Linear Decision Rule, Goal Programming, Heuristics, and Simulations, among others. The publication allows the reader to determine what pertinent research exists to identify the model best suited to a specific type of problem or to inform a desired solution methodology (Nam and Logendam, 1992).

2.8 Conclusion

In conclusion, the authors of the cited works provide a robust analysis that is highly applicable to the problem statement and description. There is ample research into the proposed field to warrant further investigation that meets the requirements of the problem statement while providing an opportunity to employ various relevant modeling techniques. The most relevant models included mixed integer linear and non-linear programs that sourced either empirical models or stochastic modeling in order to develop a solution that met the required parameters. Models that represented cascading network effects will supply the depth of research necessary to determine where the most significant impacts of refined petroleum disruption will occur. There was significant diversity of the operations research solutions applied to this field. Almost every tool in the operations research field is applicable to some portion of the petroleum production, refinement and distribution problem.

Specifically, empirical modeling was the most prominent approach used to explore and predict price variations. Linear programming and mixed integer programming applied well to refinery mix problems and the network flow problems needed to optimize productivity for the refiners and distributors. Stochastic methods were most applicable to apply uncertainties related to demand parameters, supply disruption events, and variations in price and stock price influencers. Heuristics were present throughout as a method of improving computational efficiency. Network interdiction utilized a composite of large scale optimization and adversarial programming techniques. Cascading effects models are beginning to implement more specific network models that could inform the capabilities of a model in a manner that addresses the problem statement.

III. Methodology

3.1 Introduction

The focus of the recommended methodology is an investigation of a realistic refined petroleum network model, determining the effects of interdiction, and tracing the cascading effects through adjacent and dependent industries. The models used build on sources from Chapter II and will define a process for analysis of scenarios from a relevant case study.

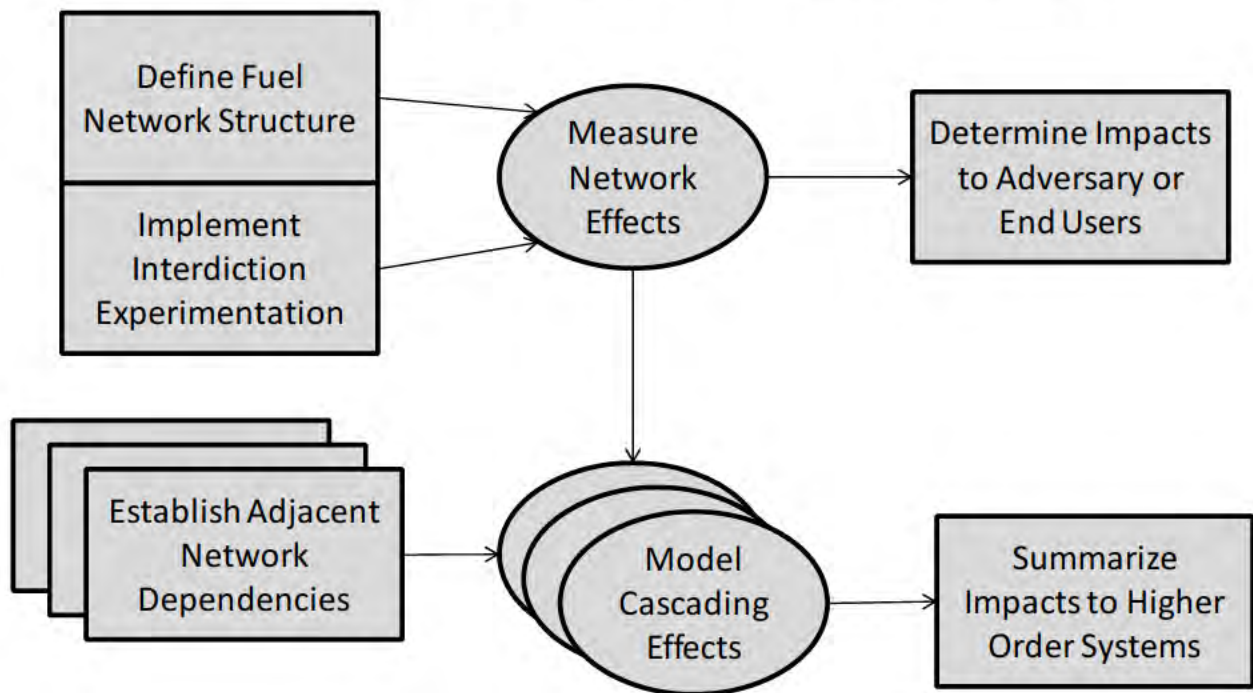


Figure 3: Problem Framework

The methodology presented in Figure 3 is used to analyze the cascading impacts of a fuel network interdiction and the cascading effects through multiple adjacent industries. The initial phase is the disruption of the fuel supply with a purpose of preventing an adversary from achieving access to energy. The effects of this disruption will impact other users of that resource, which will reverberate through military, social, and economic systems of the regional or national economy. A reasonable estimate of the net impact of this disruption on the local

and regional economies will enable decision makers to consider the ramifications of such an intentional disruption.

3.2 Development of a Petroleum Commodity Network Flow

In the traditional models presented by Pinto *et al.* (2000) and Neiro and Pinto (2004), the refiner is concerned with maximizing profit while meeting contractual market demands without violating the balance of storage capacities. Storage capacities are of primary concern due to the hard constraint that limits shipments to the minimum and maximum volumes that the containment units of any one location can physically hold. The model presented by Pinto *et al.* defines the profit function as revenues less the sum of the stock cost of crude oil, transportation costs, holding costs, and delivery costs (Pinto *et al.*, 2000) This model is realistic for most refinery networks in normal circumstances.

However, an adversary is likely to alter this model in order to provide the necessary resources for military operations and basic government and civilian function during a period of anticipated or actual conflict. Alterations to the profitability model are particularly likely when the adversary possesses a state run NOC. This strategic model uses a prioritized optimization that maximizes dispersion to key locations using concepts from aggregate planning by providing available resources to critically vulnerable or essential petroleum users. If implemented carefully, an adversary would only execute prioritization to prevent or mitigate a physical shortage in order to preserve the integrity of steady state operations for as long as reasonably possible. The profit function is instead relegated to a constraint on financial resources imposed by circumstances on the adversary, should any practical constraint exist.

3.2.1 Network Formulation Problem Statement

This formulation will develop the mathematical program required to route multiple types of refined petroleum products from a supply point at a refinery or import depot through a pipeline network for storage or consumption at demand locations. Transshipment nodes have the ability to store products, distribute to end users, or ship to subsequent demand locations in the network. The objective is to maximize flow of each product type to each demand node with weighted preference assigned to locations that are critical to the network manager.

3.2.2 Definition of Terms

The terms used in the formulation are defined in Table 1. These terms will remain consistent throughout this thesis report. Any application of this methodology or its terms is applied across a consistent time period. The model is developed for a specific time period and incrementally solved for each subsequent time period within the model. The analyst must standardize all terms including flow rates, demand requirements, and supply in accordance with the selected time period. This investigation will consistently utilize a daily time period that explores a 90 day time horizon. Therefore, the model considers a 90 day time horizon and optimizes in daily time periods. All terms in Table 1 are continuous unless otherwise noted.

Table 1: Index of Network Model Terms

Sets	Definition
$j \in D$	Set of all Demand Nodes j in a Directed Network
$(m,n) \in A$	Set of Directed Pipeline Arcs in Network from node m to node n
$D_j = \{f \in D : (j,f) \in A\}$	Set of all nodes f immediately following node j in a directed network
$H_j = \{h \in D : (h,j) \in A\}$	Set of all nodes h immediately preceding node j in a directed network
$i \in S$	Set of Supply Nodes i
$S_j = \{r \in S\}$	Set of Refinery Supply Nodes r providing refined products to node j
$E_j = \{e \in S\}$	Set of Import Supply Nodes e providing refined products to node j
$p \in K$	Set of Petroleum Products p
Decision Variables	Definition
$Q_{i,p}$	Ratio of expected product p demand delivered to demand node j
$y_{m,n,p}$	Flow Rate for arc (m,n) for product p from node m to n
$\Delta Stor_{i,p}$	Inventory change of product p storage at node j to adjust available stocks
$RS_{i,p}$	Refinery output of product p at supply point i
$IS_{i,p}$	Imported delivery of product p at supply point i
$SCons_{j,p}$	Shortfall in End User Consumption of product p at node j
Constants	Definition
$w_{i,p}$	Weighted value to network manager for product p at node j
$IStor_{i,p}$	Initial storage inventory of product p at node j updated each time period
$Dem_{i,p}$	Total expected Demand of product p at node j
$StorCap_{i,p}$	Storage capacity for product p at node j
$LBStorCap_{i,p}$	Minimum storage capacity for product p at node j
$RCap_{i,p}$	Refinery capacity of product p at supply node i
$ICap_{i,p}$	Import capacity of product p at supply node i
$LBFO_{m,n}$	Minimum Flow Rate for arc (m,n) for all products p
$FO_{m,n}$	Maximum Flow Rate for arc (m,n) for all products p
$Cons_{j,p}$	End User Consumption at node j of product p

3.2.3 Maximum Flow Mathematical Programming Formulation

The complete formulation is defined in Table 2 and represents the mathematical model that will enable an assessment of a petroleum product supply network in the event of a disruption. The model uses a daily period for this study that accumulates over a 90 day time horizon beginning at the time of disruption with the potential for a suitable warm-up period.

Table 2: Complete Refined Petroleum Flow Network Mathematical Model

$$\max_{Q,y,\Delta Stor,RS,IS,SCons} \left(\sum_{p \in K} \sum_{j \in D} Q_{j,p} Dem_{j,p} w_{j,p} \right) \quad (3)$$

$$\text{subject to: } LBO_{m,n} \leq \sum_{p \in K} y_{m,n,p} \leq FO_{m,n} \quad \forall (m,n) \in A \quad (4)$$

$$Cons_{j,p} + \Delta Stor_{j,p} - SCons_{j,p} = Q_{j,p} Dem_{j,p} \quad \forall j \in D, \forall p \in K \quad (5)$$

$$LBStorCap_{j,p} \leq \Delta Stor_{j,p} + IStor_{j,p} \leq StorCap_{j,p} \quad \forall j \in D, \forall p \in K \quad (6)$$

$$RS_{i,p} \leq RCap_{i,p} \quad \forall i \in S, \forall p \in K \quad (7)$$

$$IS_{i,p} \leq ICap_{i,p} \quad \forall i \in S, \forall p \in K$$

$$\sum_{h \in H_j} y_{h,j,p} - \sum_{f \in D_j} y_{j,f,p} - Cons_{j,p} - \Delta Stor_{j,p} + SCons_{j,p} = 0 \quad \forall j \in D, \forall p \in K \quad (9)$$

$$\sum_{h \in H_j} y_{h,j,p} - \sum_{f \in D_j} y_{j,f,p} - Cons_{j,p} - \Delta Stor_{j,p} + SCons_{j,p} + \sum_{r \in S_j} RS_{r,p} + \sum_{e \in E_j} IS_{e,p} = 0 \quad (10)$$

$$\forall p \in K, \forall j \in D$$

$$y_{m,n,p} \geq 0 \quad \forall (m,n) \in A, \forall p \in K \quad (11)$$

$$SCons_{j,p} \geq 0 \quad \forall j \in D, \forall p \in K \quad (12)$$

$$RS_{i,p} \geq 0 \quad \forall i \in S, \forall p \in K \quad (13)$$

$$IS_{i,p} \geq 0 \quad \forall i \in S, \forall p \in K \quad (14)$$

3.2.4 Objective Function Development

This maximization function requires a term that ensures each essential distribution node receives a decision variable, $Q_{j,p}$ that indicates the percentage of the expected local demand of product p that node j will receive. In this model, the variable $Q_{j,p}$ represents a multiplier of demand that assigns the delivery volumes to each node j . When $Q_{j,p}$ is set to 1, the product

receipts at the indicated node will equal the expected demand. Should $Q_{j,p}$ exceed 1, the product receipts will exceed expected demand and allow for addition to the storage volume of the demand location for product p . Because maximization of storage is essential to a robust network, increasing or maintaining storage levels at critical nodes is a key management tactic in the event of an anticipated network interdiction. The effect of the $Q_{j,p} Dem_{j,p}$ formulation is to determine the total deliveries to the storage point at each period. This objective function decision variable will effectively maximize the commodity flow rate in a manner that best meets the strategic interests of the network manager. The model determines the most appropriate value for $Q_{j,p}$ subject to constraints, weightings, and bounds set by the analyst.

The model can determine a positive value that is less than 1 to represent $Q_{j,p}$. This result will reduce the product deliveries below the expected demand level and require withdrawals from inventory storage in order to meet local consumption requirements. The sum-product of the $Q_{j,p}$ variable with an appropriate scalar for weight $w_{j,p}$ and the product demand at each node j from its nearest supplier provides the maximization function directing the adversary's distribution plan. This allows non-critical nodes to receive daily demand and available surplus as long as feasible. This function also allows the model to incorporate what an adversary might attempt to implement in regards to limited resources and distribution capacity because the analyst can bound $Q_{j,p}$ in order to limit the size of deliveries or withdrawals. However, since the future interdiction plan may have vastly different objectives than the distribution network manager, the maximized flow uses the $Q_{j,p}$ multiplier as a decision variable. The key output will describe the time requirement for an adversary to increase the robustness of their system to deal with specific demand goals. The adversary can maximize the amount of refined products that are diversified across the storage capacity of critical locations. Once a disruption occurs,

the formulation will continue to assign maximum flow to critical nodes where the infrastructure to complete commodity shipments is still functional.

If appropriate to meet the needs of the decision maker, the network manager may allow the value of the variable $Q_{j,p}$ to become a negative multiplier. This negative multiplier will force less critical supply nodes to remove $Q_{j,p}$ percentage of supply from storage and inject that quantity back into the network. In the event that no supply points can reach a critical node, appropriately assigning a negative $Q_{j,p}$ value to a preceding demand node will allow critical nodes to receive shipments from all remaining accessible locations in the network despite a successful cut of the network topography.

The floating ceiling system of storage used in most storage facilities coupled with the access location of the fuel spigot renders approximately 20% of the storage contents inaccessible without causing significant damage to the storage cell (Pinto *et al.*, 2000). For this study, the value of $Q_{j,p}$ for an undisrupted fuel storage facility is restricted by this lower capacity bound. The requirement could be removed entirely should it be appropriate in a prolonged scenario, which allows the model to consider any feasible continuous value for the variable, $Q_{j,p}$.

The refiner will assess the criticality based on location of demand node j where delivery is required. This criticality will result from its distance from the nearest supply node and its value contribution to supported military and civilian assets. In order to differentiate between the criticality of nodes included in the network, the weight multiplier, $w_{j,p}$ is included to determine appropriate prioritization amongst critical nodes selected for a variable value of $Q_{j,p}$ $Dem_{j,p}$. The value of $w_{j,p}$ results from an assessment of the criticality of the node and the perceived difficulty in maintaining its supplies. For non-essential nodes, the $Q_{j,p}$ variable is

initially modeled near 1 in order to resemble a steady state operation. The results of this maximization function are presented in Equation (3). An assessment of criticality of demand locations is necessary to inform the weighted assessment that will appropriately implement the network priorities. This information may be available from intelligence sources, remote observations of the system, or known locations of critical infrastructure and military capabilities.

$$\max_{Q,y,\Delta Stor,RS,IS,SCons} \left(\sum_{p \in K} \sum_{j \in D} Q_{j,p} Dem_{j,p} w_{j,p} \right) \quad (3)$$

3.2.5 Description of Constraints

These data sets inform the constraint set for operation of the network. Equation (4) is the defining constraint of flow capacity over a time horizon consistent with the model. For this case study, the model will implement a daily iteration of a 90 day decision cycle. The amount shipped by each node through an available arc (m,n) on a specific time period within the planning range must not exceed the flow capacity of that arc denoted by $FO_{m,n}$. The flow rate to each demand node, j is determined by the summation of product types, p moving through delivery pipeline arc (m,n) from the previous node iterated over a consistent time interval and defined as $y_{m,n,p}$. Additionally, since the arc represents a polyduct, all product shipments must traverse the same arc within the network infrastructure. Since polyduct capacity will often mirror or exceed the capacity of the supply points, this may not be a determining factor. However, if available arc capacity, $FO_{m,n}$ decreases as products progress through the system, this constraint should be extended to all locations with arc capacity restrictions. There is also a possibility of a lower bound flow rate, $LBFO_{m,n}$ that dictates a minimum flow rate to ensure continued operation of the polyduct arc (m,n) (Pinto *et al.*, 2000). This constraint will

contribute significantly to the behavior of the system in the event of an interdiction, and requires flow to stop completely if it cannot attain a certain minimum operation.

$$LBFO_{m,n} \leq \sum_{p \in K} y_{m,n,p} \leq FO_{m,n} \quad \forall (m,n) \in A \quad (4)$$

In all cases where demand locations are accessible by the distribution network, the shipments may satisfy daily demand if $Q_{j,p}$ is appropriately constrained. Even in the event of an impending interdiction, the availability of supplies is essential to the stability of the network and the economy it supports. Therefore, the network manager may continue to meet demand until it is no longer feasible if the goal is to limit secondary economic effects. In this case, $Q_{j,p}$ is constrained at or above 1. If the network managers desire to reduce the deliveries to a particular node, $Q_{j,p}$ may be constrained below 1, which will force the node to meet consumption requirements, $Cons_{j,p}$, by removing a volume from storage, $IStor_{j,p}$ until storage volumes are depleted. In this model, the variable for storage adjustments, $\Delta Stor_{j,p}$ is not restricted to positive values and can affect the storage volume negatively or positively. Equation (5) enforces this constraint by maintaining or depleting the storage capacity of a node as necessary to meet distribution objectives.

An essential consideration to this analysis is to determine the ability of the system to meet local consumption requirements. Since the shortfall in this local demand will manifest itself in cascading failures within dependent systems, the model should record the presence and quantity of demand shortfall across all demand nodes. Price adjustments may impact the demand levels in local markets. However, market driven demand reductions may not diminish the existence of shadow demand if local prices impede the volume of the products available for purchase. The lack of available supplies to support the economy and its dependent industries will negatively impact sector productivity. This result will dictate the severity and location for

sources of future cascading effects (Lee *et al.*, 2000). The equality constraint in equation (5) captures the magnitude of demand shortfall, $SCons_{j,p}$ in consumption requirements at each node, j for product, p based on known or expected demand levels for the daily time period consistent with the model. This shortfall is bounded between zero and the consumption parameter, $Cons_{j,p}$ at node j across a time factor that is consistent with the model.

$$Cons_{j,p} + \Delta Stor_{j,p} - SCons_{j,p} = Q_{j,p} Dem_{j,p} \quad (5)$$

$$\forall j \in D, \forall p \in K$$

Storage adjustments calculated by the sum of the product quantity change and the initial storage quantity at each node, j for product, p must be non-negative or greater than the minimum storage volume, depending on the site configuration. As previously noted, a floating ceiling storage cell requires approximately 20% minimum capacity to avoid damage to the system (Pinto *et al.*, 2000). This adjustment to the storage minimum can be included if applicable to the network and is summarized in equation (6). The decision variable, $\Delta Stor_{j,p}$ determines the volume adjustment of product inventory by type during shipments in the time period. $\Delta Stor_{j,p}$ is calculated as the equality between the amounts shipped less the amount added to storage and the demand for that product p at the specific distribution node j . Equation (6) defines this equality function and provides an essential component of the model. This storage adjustment is required to update the model at specified periods over a time horizon. The change to storage volumes will become the new initial storage constraint, $IStor_{j,p}$ in the subsequent time period during the model run.

$$LBStorCap_{j,p} \leq \Delta Stor_{j,p} + IStor_{j,p} \leq StorCap_{j,p} \quad \forall j \in D, \forall p \in K \quad (6)$$

Supply constraints require that the supply shipments from each supply node do not exceed the known capacity of that node reduced by the amount of demand received directly at

the point of refinement. Equation (7) maintains that refinery points, RS_i , cannot ship to demand node j beyond their capacity to produce refined products of each type p . The refinery locations maintain local supply and distribution points that can ship products as individual storage nodes within the network. The representation of these storage nodes does not differ from other transshipment nodes in the network defined as a node, j . This capacity constraint is represented as $RCap_{j,p}$. A similar constraint shown in equation (8) is necessary for importation nodes, IS_i which cannot provide input to the system that is greater than available capacity, $ICap_{i,p}$ for any product p at supply node i .

$$RS_{i,p} \leq RCap_{i,p} \quad \forall i \in S, \forall p \in K \quad (7)$$

$$IS_{i,p} \leq ICap_{i,p} \quad \forall i \in S, \forall p \in K \quad (8)$$

Balance constraints will dictate the movement of petroleum products through the system. This balance constraint ensures that all flows of products, p through the polyducts are stored, consumed, or shipped to subsequent demand nodes, f . Additionally, the network manager can ship storage volumes back into the system to reallocate inventory levels. This flow balance is represented as a free body diagram centered on demand node j and is depicted in Figure 4.

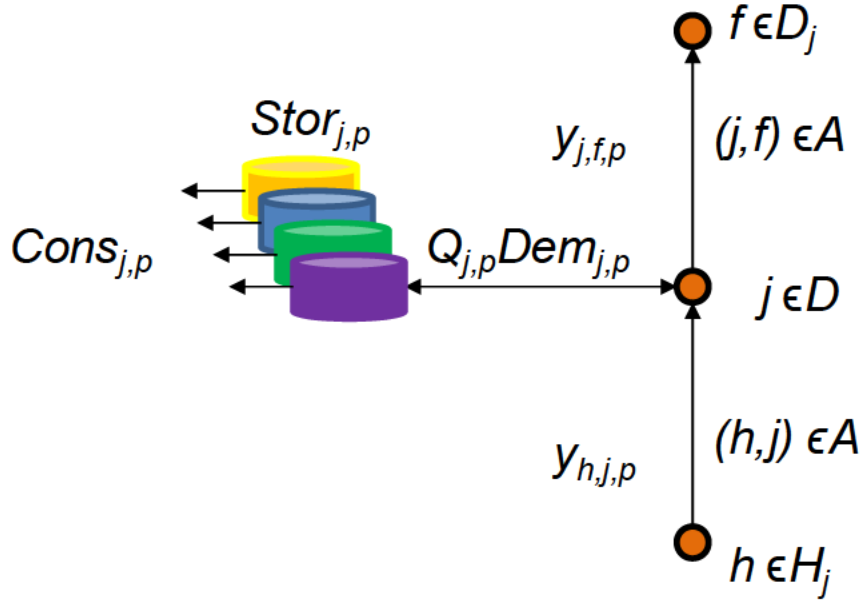


Figure 4: Free Body Diagram Representation of Flow Balance

These balance constraints enforce conservation of flow through each demand node, j . For pure demand nodes, this constraint is defined by equation (9) and includes the inflow from the sum of all connected inbound nodes, h as the source for each product type, p defined as the summation of $y_{h,j,p}$. The $Q_{j,p} Dem_{j,p}$ parameter is present to determine the quantity of each type of product that enters or leaves the pipeline network, represented as a ratio, $Q_{j,p}$ of the total expected demand of product p at node j . This quantity enters or leaves the pipeline to account for the total amount of each product interaction with the system for consumption or changes to storage capacity. In the flow equation, $Q_{j,p} Dem_{j,p}$ is represented by the product consumption, $Cons_{j,p}$ and the change in storage quantity for each node, $\Delta Stor_{j,p}$. The remaining amount is the summation of $y_{j,f,p}$ that is subtracted to account for the amount of each type of product shipped to each of the immediately subsequent demand nodes, f in the network. A shortage variable, $SCons_{j,p}$ is also included to account for situations where consumption requirements are

unavailable. Equation (9) summarizes this conservation of flow for each pure demand node at each time period across a time horizon.

$$\sum_{h \in H_j} y_{h,j,p} - \sum_{f \in D_j} y_{j,f,p} - Cons_{j,p} - \Delta Stor_{j,p} + SCons_{j,p} = 0 \quad \forall j \in D, \forall p \in K \quad (9)$$

Refinement or import nodes may have to satisfy some level of local demand directly from stocks in their storage depot. Therefore, the conservation of flow for each source node will augment equation (10) with the addition of importation, $IS_{e,p}$ or refinery supply, $RS_{r,p}$ that is injected into the network from that supply node, i . The augmentation of these supply nodes is depicted in the free body diagram shown in Figure 5. The depiction adds the supply nodes, which feed a demand node, j that represents the local refinery storage infrastructure or import/export terminal storage points. Once the addition of supply parameters is added to the conservation of flow, the demand point behaves identically to other demand points along the distribution network by shipping to subsequent locations according the parameters dictated by the $Q_{j,p}Dem_{j,p}$ model.

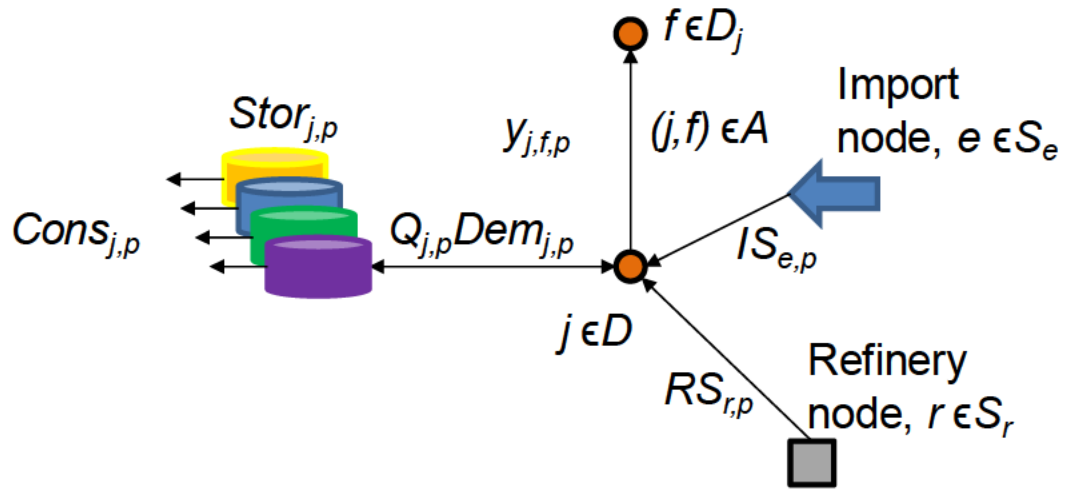


Figure 5: Free Body Diagram Representation of Conservation of Flow Including Supply

Since refineries are often dispersed throughout a petroleum distribution network, the supply node conservation is only essential where production or importation is a possibility. Therefore, an input of zero can represent these parameters if the facility is not present or offline. This balance equation ensures that the refinery products rendered locally or imported are injected into the network appropriately and shipped to the subsequent nodes in the system.

$$\sum_{h \in H_j} y_{h,j,p} - \sum_{f \in D_j} y_{j,f,p} - Cons_{j,p} - \Delta Stor_{j,p} + SCons_{j,p} + \sum_{r \in S_j} RS_{r,p} + \sum_{e \in E_j} IS_{e,p} = 0 \quad (10)$$

$$\forall p \in K, \forall j \in D$$

Non-negativity constraints will inform several of the decision variables that are included in equations (13)-(14). Decision variables not indicated in this equation set are not constrained in sign.

$$y_{m,n,p} \geq 0 \quad \forall (m,n) \in A, \forall p \in K \quad (11)$$

$$SCons_{j,p} \geq 0 \quad \forall j \in D, \forall p \in K \quad (12)$$

$$RS_{i,p} \geq 0 \quad \forall i \in S, \forall p \in K \quad (13)$$

$$IS_{i,p} \geq 0 \quad \forall i \in S, \forall p \in K \quad (14)$$

3.2.6 Summary of Mathematical Model

The *Q-Demand* model is designed to iterate for an appropriate time horizon as selected by the modeler, so long as the time delineation is consistently applied across all variables. For the case study and implementation in this research, the model iterates using a daily time period over a 90 day planning horizon starting at the time of disruption. The modeler may also chose to assign an appropriate warm up period in order to replicate the network manager's capacity to build up the inventory level of supplies. Optimizing this model without interdiction of the network enables the modeler to represent the warm-up period between the network manager's implementation of aggregate inventory planning in order to diversify their supply status through

the anticipated time of interdiction. However, the model is amenable to any consistent implementation of time that is sufficiently precise to properly limit the conservation of flow. The strategist can extend the model for weekly or monthly time periods as necessary to properly assess the capacities of the network.

The daily iteration of this model enables the collection of accumulated data that will inform potential strategies for interdiction. The model produces data for supply availability at each location and unmet demand at each iteration that are critical to determining the viability of a course of action and the associated cascading effects that may accumulate using different experimental scenarios. Because the shortfall in demand, $SCons_{j,p}$ is calculated daily under the study conditions, the summation of this value across all demand nodes, j within the model will provide a snapshot of the degree that interdiction techniques have negatively impacted the local economy.

Additionally, the daily storage availability, $Stor_{j,p}$ provides a tool to measure the supply situation at critical nodes as determined by the strategic interests of the campaign planners. The measurement of this statistic summed across the time periods prior to decisive operations allows the modeler to estimate the degree to which an interdiction strategy will negatively impact an adversary's ability to maintain petroleum supplies that are accessible to critical locations. For example, this model will use a 90 day time horizon for each experimental replication. However, the onset of decisive actions by friendly forces is determined from a detailed concept of operations and will likely occur far sooner than 90 days from the interdiction. The strategist is primarily interested in the availability of military grade fuel to the adversary during the lead up to a decisive operation. For the case study in this thesis, that time period is set to 21 days from interdiction. The manipulation of the parameters within this

model will allow experimentation using various interdiction strategies. The outcome of these strategies measured in demand shortfall and fuel availability at critical nodes will inform predictive analysis on campaign effectiveness and feed the predictive model of cascading impacts.

3.2.7 Information Requirements

The planner requires significant data sources regarding supply and demand interactions. Many of these are available from open source data. This is particularly true when the refinery and distribution operations are part of a publicly traded portfolio. Statistics may be available from various sources of information.

Planners require information regarding the location and capacity of refineries and import terminals for refined petroleum products that includes daily operational data. It should be noted, however, that the network managers and their supported decision makers may forego commercial needs in the event of an emergency or disruption. Additionally, the model requires information on the demand nodes and the network architecture that connects them.

Based on the network requirements regarding fuels of military application and cascading effect, the methodology may include diesel fuel, fuel oil, and kerosene based jet fuel from the middle distillate spectrum. Gasoline is also included as a critical component due to its dominance in the refining and distribution network of most petroleum markets, as well as its implications on cascading effects (EIA, 2014).

3.3 Implementation of Multi-Commodity Flow

The initial concept necessary to establish a coherent network requires the development of the network architecture based on a multi-commodity flow. Petroleum networks will transport multiple product types across an extended network of pipelines and storage facilities.

Formulating this network into an organized model requires the establishment of a series of matrices that allow the modeler to include the layers of products and apply appropriate constraints to the system.

The formulation used by McBride (1998) accommodates a refined petroleum network using aggregate planning methodology. The establishment of a network based on multiple products traversing similar delivery infrastructure is accommodated by matrix (15). Each N_K sub-matrix in this equation takes the form of the network incidence matrix representing the flow of a specific type of petroleum product. This incidence matrix for each N_K sub-matrix includes inputs from servicing supply points, the flow balance along transshipment points, and the removal of demand at distribution nodes for each product, p . The matrix N may be as large as necessary to accommodate $|K|$ product types but grows in complexity at each addition. Furthermore, as the constraints develop, the products are restricted to the same production and distribution infrastructure.

Implementing McBride's (1998) formulation for multi-commodity flow, the N matrix will populate with each petroleum product type that is of interest to the modeler. In matrix (15), the products represented are various fuel types such as gasoline, kerosene (jet fuel), diesel, and fuel oil and denoted as N_1 through N_K respectively. These sub-matrices represent the flow equations for each product type that are implemented using an incidence matrix.

$$N = \begin{bmatrix} N_1 & & & \\ & N_2 & & \\ & & N_3, \dots & \\ & & & N_K \end{bmatrix} \quad (15)$$

Each N_K includes the information on flow balances from $|A|$ supply source inputs and between $|D|$ demand nodes. The dimensions of each sub matrix N_K require columns for each

supply point, i and polyduct arc (m,n) , that connects demand node m with n . Each demand node, j is represented in $|D|$ rows. The resulting algebraic function across each row represents the conservation of flow at each node, j within set D . The sub-matrix N_K uses inputs represented as a zero, one, or negative one value that indicates potential gains/inflow (1), lack of interaction (0), or losses/outflow (-1) for each associated infrastructure point, i , j , or (m,n) .

The flow balance presented in equation (9) and (10) only depicts a single product type, p at the specified demand node, j with inputs from supply node, i . In order to populate this conservation of flow data for the entire model, the complete equation set requires the use of matrix (15). The flow balance for each node j within an individual product type will populate the sub-matrix N_K . The modeler must represent each node within the matrix dependent upon its pipeline interactions and accessibility to supply nodes, i . This requires that the N_K sub-matrix has columns representing all supply points, i and pipeline interactions, (m,n) . The N_K sub-matrix requires a row to account for each demand node, j where the model records the conservation of flow data. These sub-matrices are then combined by creating a diagonal matrix N using sub-matrices N_K to represent each product type as defined in matrix (15). This formulation will result in an N matrix that requires dimensions of $(|S|+|A|)(|K|^2|D|)$. The potential size of this problem depends primarily on the number of product types that are considered.

3.4 Cascading Effects Analysis: Input-Output Models

Wassily Leontief pioneered the study of the equilibrium of economic interactions (Leontief 1951). This work led to the development of a wide range of applications in both energy and military modeling that inform research on the ramifications of changes in the production capabilities of an economy. The Leontief model assumes that economies take the

form of a number of interdependent sectors that purchase and sell products or commodities to and from one another. Since petroleum products are often defined as commodities (Inkpen and Moffett, 2011: 503), this application is particularly relevant to energy production and distribution. The magnitude to which local industries rely on petroleum fuel products is an essential component of a Leontief model that defines interactions within an economy. Within the Leontief model, the refinery process must produce and distribute sufficient output to satisfy local, foreign, and own use demand factors. The model is centered on an input-output matrix, A which defines the interaction in terms of monetary value between all industries of interest within a specific regional or national economy.

Leontief's model requires three critical assumptions that are applied directly to military strategy by Snodgrass *et al.* (2004). The coefficients of production, which are determined by industry requirements, must be a fixed value for the duration of the use of the model. The requirement of constant returns dictates that industry outputs change proportionally to an increase or decrease in resources provided. This is a valid assumption related to petroleum consumption, as industries utilizing these products will reduce operations proportionally to a lack in supply until a failure point is reached and complete shutdown becomes necessary (Haimes and Jiang, 2001: 6). Additionally, resources are considered homogeneous and generally measured in terms of the monetary value paid for them during the interactions between sectors (Snodgrass, et al 2004). The use of monetary values is a convenient method for assessing the interactions in consistent units of measure. An economy that includes significant top-driven decision factors within an economy may prioritize certain sectors for receipt of available resources such as fuel. This eventuality can impact the optimization objective function detailed in equation (17).

3.4.1 Definition of Terms for Leontief Input-Output Model

Table 3 describes the terms required to develop an input-output model using the Leontief mathematical programming formulation. The terms referenced in this table are not associated with any of the terms from the previous maximum flow network mathematical program.

Table 3: Definition of Leontief Input-Output Model Terms

a_{ij}	The technology coefficient for the amount of a product from sector i consumed by sector j as a percentage of total inputs required for operation of sector j
L	The matrix composed of all Leontief Coefficient elements of a_{ij} from a particular economy
x_{ij}	The amount or value of products from sector i consumed by sector j
X_i, X_j	The total outlays (requirements) and the total outputs (production) of industry i or j . Outlays and outputs must be equal in this formulation.
X	Vector composed of all values of X_j in an economy
r_{ij}	Coefficient of resources i required for use in sector j
P_j	The total resources i available to an industry j
C_j	Amount of production delivered to end users by industry j
C	Vector consisting of end user consumption across all industries in an economy
F_i	Amount of final demand from industry i
F	Vector consisting of final demand across all industries in an economy
R_i	Amount of exports from industry i
R	Vector consisting of exports across all industries in an economy

3.4.2 Formulation for Leontief Input-Output Model

Problem Statement: This Input-Output Mathematical Model determines how the productivity losses in a specific sector reverberate throughout the economy based on interdependencies between industries. The model maximizes the remaining productivity across all industries based on limitations placed upon a specific industry or industry component of the economy. This formulation is adapted from Gallagher *et al.* (2005).

Table 4: Mathematical Model for Leontief Input-Output Formulation

$$\max_{X,P} \left(\sum_{i=1}^{i=n} X_i \right) \quad (17)$$

subject to:

$$\begin{aligned} a_{11}X_1 + a_{12}X_2 + \dots + a_{1n}X_n + C_1 &\leq X_1 \\ a_{21}X_1 + a_{22}X_2 + \dots + a_{2n}X_n + C_2 &\leq X_2 \\ &\dots \\ a_{n1}X_1 + a_{n2}X_2 + \dots + a_{nn}X_n + C_n &\leq X_n \end{aligned} \quad (19)$$

$$\begin{aligned} r_{11}X_1 + r_{12}X_2 + \dots + r_{1n}X_n + C_1 &\leq P_1 \\ r_{21}X_1 + r_{22}X_2 + \dots + r_{2n}X_n + C_2 &\leq P_2 \\ &\dots \\ r_{n1}X_1 + r_{n2}X_2 + \dots + r_{nn}X_n + C_n &\leq P_n \end{aligned}$$

$$\sum_j^{j=m} P_j \leq \sum_i^{i=n} R_i + \sum_i^{i=n} F_i \quad (20)$$

$$\begin{aligned} X_i &\leq X_i^* \quad \text{for } i = 1, \dots, n \\ P_j &\leq P_j^* \quad \text{for } j = 1, \dots, m \end{aligned} \quad (21)$$

This matrix is then configured as technology coefficients calculated using equation (16). Technology coefficients, a_{ij} are determined by dividing the amount of sector i outputs consumed in sector j , x_{ij} by the total output of sector i , X_j . All x_{ij} elements of this equation are measured in values of the interactions measured by some monetary standard. Each entry in the input-output matrix, L is converted to a Leontief coefficient using this equation. The resulting technology coefficient a_{ij} represents the proportion of total outlays of industry j that are consumed by dependent industry i . Restated, this represents the level of input requirements obtained from a specific industry as a percentage of total inputs into that industry, which are

defined as their total outlays, or intermediate consumption. The L matrix is simply an organization of each Leontief coefficient, a_{ij} (Gallagher *et al.*, 2005).

$$a_{ij} = \frac{x_{ij}}{X_j} \quad i = 1, \dots, n, j = 1, \dots, m \quad (16)$$

Casler and Wilbur related this concept specifically to the energy industry using a model that defines energy intensity as an interaction term within the input-output analysis. This concept measures the interaction between energy and non-energy sectors in terms of units of thermal intensity per unit of cost. The authors propose that the technology coefficients represent input-output measurements defined by thermal intensities and their costs in dollar amounts rather than the Leontief technology coefficients that aggregate every input-output matrix entry as a strictly financial interaction (Casler and Wilbur, 1983).

Haines and Jiang (2001) define the risk of inoperability as the result of reduced output causing systemic failures in a dependent industry due to a measureable disruption in the interconnected systems. The risk model approach uses an L matrix that defines the Leontief coefficients using the risk of inoperability of a particular infrastructure system caused by a direct disruption in an interconnected industry. Likewise, resource availability and supply are quantified by the risk of inoperability rather than direct inputs as in the traditional formulation. This model is adaptable for disruptions that are undefined or stochastic in nature (Haines and Jiang, 2001).

Although this formulation of Leontief models is highly useful for the implementation of interactions between critical networks, its main impact is to measure the risk of a disruption within various industries. In a follow on article, Haines *et al.* (2005) further discuss the versatility of the inoperability measurements utilized in various Leontief models. The authors

discuss how inoperability may be measured for application to various types of problems.

Inoperability may extend to shortfalls in production, percentages of demanded production, and the residual production of a disrupted system (Haimes *et al.* 2005). The article further describes how the L matrix in the Leontief model is derived from appropriate construction of *make* and *use* matrices. The make matrix describes industrial commodity production, while the use matrix describes the consumption of these same commodities within industries as a requirement for their productivity.

The Leontief input-output model requires an appropriate optimization function that approximates the expected actions and prioritization of the adversary. There is significant variation in the impact based on how the network manager might redistribute available resources. The manager could elect to maintain production across the economy by implementing the maximization of X_i as defined in equation (17). Alternatively, the manager could seek to preserve final demands, F_i using equation (18). Any combination of these components or weighted objective function would allow the modeler to determine the cascading impacts utilizing the most appropriate objective function for the expected actions of the network manager (Gallagher *et al.*, 2005). Investigation of these outcomes can extend into sensitivity analysis. This survey will implement equation (17) in order to maintain production across all industries in a manner that measures associated cascading effects.

$$\max_{X,P} \left(\sum_{i=1}^{i=n} X_i \right) \quad (17)$$

$$\max_{X,P} \left(\sum_{i=1}^{i=n} F_i \right) \quad (18)$$

For this study, each experimental run using the model in Table 2 will report a cumulative tally of unmet demand across the scenario. The model will assign a price to this

unmet demand based on the market value of the economic losses caused by the disruption. This output will inform the appropriate setting for the constraint X_i^* that is associated with the refined petroleum market as shown in equation (21). This limitation will reduce the contributions to the economy of refined petroleum products below its known operating levels.

Haimes and Jiang (2001) generated an application of the Leontief model that adapts the input-output framework to Interdependent Infrastructure problems that are relevant to the United States and other global economies. This approach implements a methodology for determining the risk to critical infrastructure caused by interdependence of industries (Haimes and Jiang, 2001). This model allows for the addition of r_{ij} that indicates the resource requirement i contribution to the j th infrastructure. Resources include independent requirements such as labor. The variable C_k and its associated vector C represent the sector k production outputs that are delivered to market and consumed by the sum of all end users. End user consumption is not included in intermediate consumption, which is the use of an input in the production of another product. The model accounts for intermediate consumption between industries in the L matrix and end user consumption in the C vector.

The problem methodology presented in Table 2 for modeling the capacities of petroleum distribution network will provide a deterministic output that estimates the magnitude of a disruption. Therefore, the complexity of the risk assessment criteria and determination used by Haimes and Jiang (2001) is insufficient to inform the Leontief model. Alternatively, Gallagher *et al.* (2005) present an approach that considers the direct impact of military strategy on an industry and its cascading effects throughout an economy using the formulation presented by Haimes and Jiang (2001). This representation characterizes the balance equations by

assessing the magnitude of each sector interaction and is described in equation set (19). The parameter P_n is the measurement of primary resource availability (Gallagher *et al.*, 2005).

$$\begin{aligned}
a_{11}X_1 + a_{12}X_2 + \dots + a_{1n}X_n + C_1 &\leq X_1 \\
a_{21}X_1 + a_{22}X_2 + \dots + a_{2n}X_n + C_2 &\leq X_2 \\
&\dots \\
a_{n1}X_1 + a_{n2}X_2 + \dots + a_{nn}X_n + C_n &\leq X_n
\end{aligned} \tag{19}$$

$$\begin{aligned}
r_{11}X_1 + r_{12}X_2 + \dots + r_{1n}X_n + C_1 &\leq P_1 \\
r_{21}X_1 + r_{22}X_2 + \dots + r_{2n}X_n + C_2 &\leq P_2 \\
&\dots \\
r_{n1}X_1 + r_{n2}X_2 + \dots + r_{nn}X_n + C_n &\leq P_n
\end{aligned}$$

In order to adapt this to the constrained resource environment associated with the implementation of a military strategy, the authors add flow equation (20) that constrains P_j resource requirements from exceeding the sum total of its components, final demand, F_i and Exports, R_i within the trade structure of the country (Gallagher *et al.*, 2005). This constraint is potentially relevant to a major exporter of refined petroleum, as it takes into account the implementation of trade sanctions that limit an adversary's ability to generate income through trade. This income loss will cascade through the system in a similar method of other industrial losses.

Finally, Gallagher *et al.* (2005) present additional constraints to allow for the restriction of available commodities caused by sector disruptions as a result of military strategy implementation. These constraints prevent production, X_i or resources, P_j from surpassing the imposed limitations that are the result of such an implementation, defined as X_i^* and P_j^* and are summarized in equation (21).

$$\sum_j^{j=m} P_j \leq \sum_i^{i=n} R_i + \sum_i^{i=n} F_i \tag{20}$$

$$\begin{array}{l} X_i \leq X_i^* \\ P_j \leq P_j^* \end{array} \quad \text{for} \quad \begin{array}{l} i = 1, \dots, n \\ j = 1, \dots, m \end{array} \quad (21)$$

Since input-output data often resources annual statistics, the analyst must properly scale all experimental inputs. For example, if the measured value of economic loss investigates a cumulative 90 day time period similar to this methodology, the model must properly scale the value of the response to accommodate an I-O matrix with yearly data. This requirement may violate Leontief's assumption that input-output interactions remain static in the short term, but use of a consistently accumulated data set is essential to achieving a coherent result. The objective function from equation (17) assigns the reduced level of resources amongst dependent industries. This model will determine the new operating levels for each industry as a percentage of their known economic contributions, X_i .

3.5 Interdiction Experimental Design

The interdicting force may have almost unlimited options within the parameters of their capabilities in order to disrupt a supply network. Operational experimentation provides a framework to determine methods of exploring the decision space. Experimentation involves tests of a system in an effort to determine changes to a response. The experimenter can adjust inputs to affect changes on the response that are observed in the system (Montgomery, 2013: 1-3). In the network distribution system that is modeled using the methodology outlined in Section 3.2, the experimenter is interested in what interdiction courses of action might result in desired variations to product availability to adversarial forces. Additionally, these courses of action could result in cascading effects that are more difficult to predict.

A factor is a variable that the experimenter can change. Factorial Design includes the consideration of multiple factors that are adjusted simultaneously within an experimental space.

The analysis of multiple simultaneous factors is often summarized in an T^k design. A modeler selects k number of factors and assesses them at increasing levels, T from low to high for each selected factor. In a system where variation is a factor, replications of the same experiment may occur (Montgomery, 2013: 5-7). The use a full-factorial design is most appropriate to consider the largest possible portion of the design space. In computer experimentation, full factorial designs are appropriate if sufficient time and computing power is available to implement all possible factor settings. However, in a deterministic model that does not contain stochastic or randomly selected variables, there is no presence of noise or error to consider. An augmentation of the deterministic model from Table 2 will include variations in down time imposed by interdiction that will introduce variation into this experiment.

3.5.1 Factor Selection

The interdictor has multiple courses of action that could allow disruption of the supply network in accordance with the appropriate operational plan. Appropriate factors required to analyze the decision space for petroleum network interdiction include disruptions on polyducts represented as arcs, storage hubs represented as transshipment nodes, or refinery and importation points represented as supply nodes.

Polyducts require pumping infrastructure at their origin and at intermittent locations along the route. Pumps, compressors, actuators, and the power plants that fuel them are necessary throughout a polyduct network (Miesner and Leffler, 2006: 240-258). Variations in topography could also necessitate booster locations that elevate the network flow. (Miesner and Leffler, 2006: 72-73). These physical infrastructure points often lie above ground to facilitate maintenance, and are therefore vulnerable to an interdiction strike.

Storage capacity is often limited within the refined product distribution network. Refined fuels have a limited shelf life before they begin to degrade. Additionally, storage capacity is expensive under normal circumstances. Excess storage would be financially disadvantageous to the distributor to transport excess product and store it for long periods of time. Finally, many countries lack the refinery capacity to meet local demand. In some cases, expensive importation processes must already occur to meet local demand (Inkpen and Moffett, 2011: 476-477). Therefore, it is rarely to the advantage of the refiner or local economy to import fuel that is significantly beyond required demand unless there is a significant discount rate that enables financial viability.

The middle distillate refinement process is also a potential interdiction target. As summarized in Chapter 2, the production of diesel is inextricable from gasoline and other refined products (Inkpen and Moffett, 2011: 440-446). The planner may resource expertise that informs a method of isolating diesel production capacity at a specific refinery location. However, this will only mitigate the disruption of products beyond the target set of middle distillates. The intensity of the disruption to non-targeted products is estimated by a uniform distribution between the maximum (b) and minimum (a) points determined by the modeler using input from experts. Interdiction of a refinery could include but is not limited to kinetic attacks, cyber attacks, air interdiction attacks, or financial isolation. Additionally, the modeler may update the results of various types of interdictions during ongoing operations in order to account for known effectiveness, battle damage assessments, collateral damage, and unforeseen tertiary impacts on production. For the purposes of this study, the impact of the interdiction on non-targeted products will use a random input from a uniform distribution between 0 and .25.

This means that a randomly assigned value will set the remaining production of gasoline at a disrupted refinery between zero and 25 percent of the previous capacity.

Finally, planners could attempt to implement an embargo against petroleum imports as discussed in Chapter 1. The success of an embargo depends upon the cooperation of multiple partner countries and third parties as evidenced by incidents in Iran and Iraq during the 20th century (Yergin, 1992: 464, 773). A uniform distribution between a maximum (b) and minimum (a) threshold of embargo success can provide the model with an estimate for the effectiveness of such an embargo. As evidenced from the embargo policy employed by the United States in Libya in 1986 and presented in Section 1.2, even a very successful embargo is not likely to prevent a petroleum rich adversary from exporting petroleum or its derivatives to resource hungry clients. Therefore, the modeler must make a determination of the range of effectiveness of a proposed embargo based on the most current political, diplomatic, and military circumstances of all involved players. For the purposes of this study, the impact of the interdiction on targeted products will use a random input from a uniform distribution between .1 and .25. This means that a randomly assigned value will set the remaining importation of middle distillates at a disrupted refinery between 10 and 25 percent of the previous capacity.

The model represented in Table 2 contains parameters that are easily manipulated by the analyst to replicate these factors during experimentation. This holds true for all factor types. The analyst can reduce the availability of a polyduct by lowering the capacity of its flow rate, $FO_{m,n}$. This flow rate can fall as low as zero so long as the accompanying minimum flow rate receives comparable adjustments. Storage facilities have a similar capacity constraint, $StorCap_{j,p}$ and its lower bound, $LBStorCap_{j,p}$ that are amenable to adjustment according to the appropriate level of interdiction. Importation and refinement supply points both contain

capacity constraints, $RCap_{i,p}$ and $ICap_{i,p}$ that the analyst can lower according to the level of reduction that is appropriate for the strategy under consideration. Additionally, the definition of the model is sufficient to allow point specific manipulations for location, degree, and product type. The adjustment of these factors using constraints already included in the model in Table 2 will produce changes in response levels necessary to evaluate the military effectiveness and cascading impacts of the strategy.

3.5.2 Response Selection

The impact of adjusting the factors within the model is measured by recording an appropriate response from the results of the model in Table 2 (Montgomery, 2013: 2). There are two appropriate responses to answer the study questions and inform the analysis of cascading effects. The first response is the availability of middle distillate grade fuels at the critical locations at the time when the depletion of an adversary's fuel stocks is most desirable. In order to set conditions for a D-Day that denotes the beginning of decisive operations (21 days in this study), interdiction operations occur at an appropriate offset to best degrade the capabilities of a targeted adversary and seize the initiative. This disruption will deplete the ability of an adversary to conduct operations and enable the execution of decisive operations by the supported force (DA, ADP 3-0, 2011: 5). The timing of the decisive operation varies based on the supported concept of operations and is easily manipulated by summing the data points across the critical time period during the model run. The analyst can shorten the time iterations of the model in Table 2 to enable more flexibility in the selection of a critical time period.

The second response of interest is the value of commodities removed from the economy based on the shortfall in demand, $SCons_{j,p}$. This shortfall, measured for all product types p , is priced based on known data points for the economy under consideration. Cumulative data

regarding unmet demand should be collected throughout the entire period of analysis. The duration of the analyzed time period, if measured in terms of time phased force and deployment data (TPFDD), is typically 90 days. This time horizon will vary accordingly based on mission, unit preparedness, and means of transit for the deploying force (DAF, AFI 10-401, 2006: 176-178). The economic impact is measured in product value removed from the economy and informs the methodology for cascading effects.

3.5.3 Duration of Disruption

The length of the effectiveness of the interdiction lies beyond the control of the operational planner. Once an interdiction occurs on a critical resource such as petroleum production, the network manager will execute options to restore capacity. There are frequent disruptions in the course of normal operations within a petroleum distribution network consisting of refineries, pipelines, and storage hubs. These disruptions include leaks and equipment malfunctions (Miesner and Leffler, 2006: 160, 171). The networks include a capacity to repair and restore these capacities upon a disruption, and this ability extends to intentional interruptions and acts of nature. There are also alternative resources available to the network manager in order to augment the capacity of a network to circumvent disruption points. If there is sufficient rail, road, or barge capacity available, these resources can augment the capacity of an affected pipeline. However, the time, cost, and geographical constraints of these methods limit their effectiveness (Trench, 2001: 2-3).

A reasonable implementation of a restoration process is represented by the project evaluation and review technique, or PERT model applied in project management. This model utilizes a Beta Distribution in order to provide an estimate of time to completion for a project. Petroleum network restoration is adaptable to this model. The modeler requires an estimate for

the minimum, maximum, and most likely time to complete the restoration of the interdicted resource, defined as a , c , and b respectively. The Beta distribution requires these three inputs to estimate each of its two parameters, α_1 and α_2 . These distributions are estimated by formulas (22)-(26) (Epix Analysis, 2014). While this model implements the Beta Distribution to analyze recovery time, a more appropriate distribution for a case specific target set is easily applicable to this methodology. Additionally, various distributions are easily interchangeable within most automated models and simulations.

$$\mu = (a + 4b + c) / 6 \quad (22)$$

$$\alpha_1 = ((\mu - a)(2b - a - c)) / ((b - \mu)(c - a)) \quad (23)$$

$$\alpha_2 = (\alpha_1(c - \mu)) / (\mu - a) \quad (24)$$

$$Downtime = random(\beta(\alpha_1, \alpha_2))((c - a) + a) \quad (25)$$

$$Recovery = Random(exponential(Downtime)) \quad (26)$$

Each interdiction remains effective for a random time determined by the boundaries of the PERT model Beta Distribution. Once the period of inoperability is over, the network component resumes operation. The downtime of the component is determined by a random number from the Beta distribution that is multiplied by an adjustment factor, which is summarized in equation (25). The model must record the demand shortages that accrue during this time period in order to identify the effectiveness and cascading effects of the interdiction. Additionally, the calculated downtime for each interdiction is implemented to generate a random number from an exponential function using the random variable for downtime as the expected value. The results of the random number from the exponential function determines

the recovery and repair period for partial infrastructure restoration to occur. Restoration of disruption points occurs discretely and an estimate of the percentage restored for various types of interdictions is left to the modeler through the use of expert and operational analysis.

Associated levels of interdiction involves relative adjustments to the number of nodes interdicted, the degree of disruption as a percentage of capacity, and the expected duration of the disruption. Increasing levels of each interdiction action will span the decision space and inform the process regarding the factorial design. By selecting a number of critical nodes where the interdictor desires to impede product delivery, the modeler can develop reasonable options of interdiction based on the responses of demand shortfalls and supply availability at critical nodes. Pipeline, storage, refinery, and import locations are all vulnerable to disruption. The interdictor could potentially target any or all of these vulnerabilities using a variety of means. Finally, if there are re-strike capabilities available, the modeler could adjust the minimum time period of interdiction, a , to a value fixed at the latest available date for re-strike. This is particularly pertinent to disruption of arcs and nodes and may be coordinated with the proposed initiation of friendly decisive operations. Once the response data is collected and analyzed, the modeler can assess the significance of factor adjustments and the practical implications for the strategy.

3.5.4 Hypothesis Testing

The use of experimental design requires the development and testing of hypotheses that the functions of the model investigate. These hypotheses enable the modeler to investigate various parameters, factors, and settings within the model and assess response measurements that appropriately investigate the related study question. For this study, the software package JMP11 will implement a t -statistic test on the statistical significance of each factor to determine

what terms are statistically significantly contributors to changes within the response data for each experiment.

Additionally, there is potential for effects of factor interactions and quadratic relationships to have an effect on the response. Factor interactions occur when consistent settings from one independent factor affect the response at a rate that is significantly different at various settings of another factor (Montgomery, 2013: 4). It is also possible for quadratic effects to occur within the experiment that require the use of a second-order model. Second-order models include a squared regression term that best defines a model with significant curvature.

JMP11 uses a screening feature that conducts a t -statistic test in order to recommend factor terms, interaction terms, and second-order (quadratic) terms for inclusion in the analysis of variance and resulting empirical model. A summary of the t -statistic calculation for using a multiple regression hypothesis test is shown in equation (27). This equation requires the sample value of the least squares estimator, $\widehat{\beta}_j$, an estimate of the variance, $\widehat{\sigma}^2$, and the diagonal element of the input matrix, C_{jj} . (Montgomery, 2013: 465). A number of available statistical software packages including JMP can easily calculate these parameters. If the value of t_o is greater than the index value as shown in equation (28), the parameter is deemed statistically significant to accept or reject a hypothesis regarding its impact on the response. The inputs required for equation (28) include significance level, α (always .05 in this study), number of factors, k , and number of replicates, n .

$$t_o = \frac{\widehat{\beta}_j}{\sqrt{\widehat{\sigma}^2 C_{jj}}} \quad (27)$$

$$t_o > t_{\alpha/2, n-k-1} \quad (28)$$

The hypothesis tests allow the experimenter to determine which factors, interactions, and quadratic terms have significant influence on the model. This will enable an analysis of variance that determines results based on the influence of factors on the response data that is collected during experimentation. Once experimentation and data collection is complete, the use of a regression analysis and a half normal plot within statistical software will highlight factors, interactions, and quadratic terms that significantly influence the model (Montgomery, 2013: 262-263). A response surface or profile associated with the model will highlight the response behavior at various factor settings. The hypotheses investigated in the case study in Section IV are as follows:

Hypothesis 1

- When the factors are limited to supply interdictions in the scenario, measureable cascading effects may occur, but there will be no statistically significant impact on the availability of military grade fuels at all supply locations. The experiment will interdict all supply factors of importation and refinery points in order to test this hypothesis using equations (27)-(28) and measuring the impact of two supply factors, their interactions, and all second-order terms for significance.
 - $H_{1.1}$: Supply Interdictions (refinery (Z_1) and importation (Z_2)) will not significantly impact the availability of military grade fuels at the critical supply locations.
 - $H_{1.1}: Z_1, Z_2, Z_1*Z_2, Z_1^2, \text{ and } Z_2^2 = 0$
 - $H_{1.1A}$: Supply (refinery and importation) significantly impacts the availability of military grade fuels at the critical supply locations.

- $H_{1.1A}$: Z_1, Z_2, Z_1*Z_2, Z_1^2 , and $Z_2^2 \neq 0$
- $H_{1.2}$: Supply Interdictions (refinery and importation) will not significantly impact the measureable value of economic losses based on unmet demand.
 - $H_{1.2}$: Z_1, Z_2, Z_1*Z_2, Z_1^2 , and $Z_2^2 = 0$
- $H_{1.2A}$: Supply interdictions (refinery and importation) significantly impact the measureable value of economic losses based on unmet demand.
 - $H_{1.2A}$: Z_1, Z_2, Z_1*Z_2, Z_1^2 , and $Z_2^2 \neq 0$

Hypothesis 2

- Network interdiction (critical storage and delivery systems) will provide a statistically significant impact on the availability of middle distillates at critical nodes with less cascading impact than disruptions in the pipeline arcs. This hypothesis is best tested by attempting to reject the opposite statements that network interdiction will not have a significant impact on either availability or economic losses. The experiment will interdict the network factors of storage (Z_3) and pipeline (Z_4) critical infrastructure locations in order to test this hypothesis using equations (27)-(28) and measuring the impact of two network factors, their interactions, and all second-order terms for significance.
 - $H_{2.1}$: Network interdiction (critical storage and delivery systems) will not significantly impact the availability of military grade fuels at the critical supply locations.
 - $H_{2.1}$: Z_3, Z_4, Z_3*Z_4, Z_3^2 , and $Z_4^2 = 0$
 - $H_{2.1A}$: Network interdiction (critical storage and delivery systems) significantly impacts the availability of military grade fuels at the critical supply locations.

- $H_{2.1A}$: Z_3, Z_4, Z_3*Z_4, Z_3^2 , and $Z_4^2 \neq 0$
- $H_{2.2}$: Network interdiction (critical storage and delivery systems) will not significantly impact the measureable value of economic losses based on unmet demand.
 - $H_{2.2}$: Z_3, Z_4, Z_3*Z_4, Z_3^2 , and $Z_4^2 = 0$
- $H_{2.2A}$: Network interdiction (critical storage and delivery systems) significantly impact the measureable value of economic losses based on unmet demand.
 - $H_{2.2A}$: Z_3, Z_4, Z_3*Z_4, Z_3^2 , and $Z_4^2 \neq 0$

Hypothesis 3

- The disruption of refinery supply, delivery, and storage factors within the context of the scenario will have a significant impact on the military availability with the most limited cascading impacts. This experiment will inform the recommended strategy. This hypothesis is tested by attempting to reject the opposite statements that supply and network interdiction will not have a significant impact on either availability or economic losses. The experiment will interdict factors with significance in previous experiments in order to test this hypothesis using equations (27)-(28). Evaluation will include factors, interactions, and higher-order effects on the responses.
 - $H_{3.1}$: Refinery Supply and network (storage and delivery systems) interdiction in the scenario will not significantly impact the availability of military grade fuels at the critical supply locations.
 - $H_{3.1}$: $Z_1, Z_3, Z_4, Z_1*Z_3, Z_1*Z_4, Z_3*Z_4, Z_1*Z_3*Z_4, Z_1^2, Z_3^2, Z_4^2, Z_1^3, Z_3^3, Z_4^3 = 0$

- H_{3.1A}: Refinery Supply and network (storage and delivery systems) interdiction in the scenario significantly impacts the availability of military grade fuels at the critical supply locations.
 - H_{3.1A}: $Z_1, Z_3, Z_4, Z_1*Z_3, Z_1*Z_4, Z_3*Z_4, Z_1*Z_3*Z_4, Z_1^2, Z_3^2, Z_4^2, Z_1^3, Z_3^3, Z_4^3 \neq 0$
- H_{3.2}: Refinery Supply and network (storage and delivery systems) interdiction in the scenario will not significantly impact the value of economic losses based on unmet demand.
 - H_{3.2}: $Z_1, Z_3, Z_4, Z_1*Z_3, Z_1*Z_4, Z_3*Z_4, Z_1*Z_3*Z_4, Z_1^2, Z_3^2, Z_4^2, Z_1^3, Z_3^3, Z_4^3 = 0$
- H_{3.2A}: Refinery Supply and network (storage and delivery systems) interdiction in the scenario significantly impacts the measureable value of economic losses based on unmet demand.
 - H_{3.2A}: $Z_1, Z_3, Z_4, Z_1*Z_3, Z_1*Z_4, Z_3*Z_4, Z_1*Z_3*Z_4, Z_1^2, Z_3^2, Z_4^2, Z_1^3, Z_3^3, Z_4^3 \neq 0$

Hypothesis 4

- The impacts of a natural disaster disruption within the scenario will not significantly affect supply availability at critical locations or result in widespread cascading effects. This experiment will test a smaller disruption caused by a natural disaster in a localized area using a smaller set of the four potential disruption factors. The experiment tests for the impacts of electricity and utility outages impacting pumping infrastructure at storage nodes and pipelines. Additionally, the experiment includes managed disruption of an

importation and refinery point affected by a risk based shutdown. The experiment will interdict this reduced factor set in order to test this hypothesis using equations (27)-(28).

- H_{4.1}: The Natural Disaster scenario disruptions will not significantly impact the availability of fuels at the critical supply locations.
 - H_{4.1}: $Z_1 - Z_4, C(Z_1 - Z_4 * Z_1 - Z_4), C(Z_1 - Z_4 * Z_1 - Z_4 * Z_1 - Z_4), Z_1^2 - Z_4^2, Z_1^3 - Z_4^3 = 0$
 - C() indicates all possible combinations of Z_1, Z_3 , and Z_4 interactions
- H_{4.1A}: The Natural Disaster scenario disruptions significantly impact the availability of fuels at the critical supply locations.
 - H_{4.1A}: $Z_1 - Z_4, C(Z_1 - Z_4 * Z_1 - Z_4), C(Z_1 - Z_4 * Z_1 - Z_4 * Z_1 - Z_4), Z_1^2 - Z_4^2, Z_1^3 - Z_4^3 \neq 0$
- H_{4.2}: The Natural Disaster scenario disruptions will not significantly impact the value of economic losses based on unmet demand.
 - H_{4.2}: $Z_1 - Z_4, C(Z_1 - Z_4 * Z_1 - Z_4), C(Z_1 - Z_4 * Z_1 - Z_4 * Z_1 - Z_4), Z_1^2 - Z_4^2, Z_1^3 - Z_4^3 = 0$
- H_{4.2A}: The Natural Disaster scenario disruptions significantly impact the value of economic losses based on unmet demand.
 - H_{4.2A}: $Z_1 - Z_4, C(Z_1 - Z_4 * Z_1 - Z_4), C(Z_1 - Z_4 * Z_1 - Z_4 * Z_1 - Z_4), Z_1^2 - Z_4^2, Z_1^3 - Z_4^3 \neq 0$

The results of the hypothesis tests provide validation of the significance of each factor, potential interactions, and higher order effects on the measured responses in the scenario. Significant factors, interactions, and higher-order effects will inform analysis of variance in order to produce an empirical model and response surface that is representative of the system.

This validation also provides a statistically significant value of the degree economic loss in the downstream petroleum products industry by assessing a cost to the level of unmet demand. The value of this economic loss will feed an assessment of cascading effects that determines the level of impact on dependent industries. When applied to a test scenario, similar analysis can explore a number of operational strategies under investigation.

3.6 Conclusion

The methodology presented in sections 3.1-3.4 details the process for modeling the operations of a refined petroleum network using a deterministic mathematical programming technique, determining impacts of disruption through experimentation, and estimating the cascading effects using a Leontief model. The complete flow chart representing this solution methodology appears in Figure 6. The overview shows how a known network architecture and data set populate a network implementation model. This model conducts a appropriate warm-up period to assess the impacts of network management priorities. Experimental factors and restoration inputs then populate the experimentation phase. The model records responses of military availability and economic loss on a defined timeline for the analyzed scenario. All time period solutions update the data set inputs for the subsequent time period. The results inform a Leontief input-output model with a snapshot of effects for the defined time period and allow an evaluation of strategic and economic impacts. The combination of these assessments informs the development of courses of action that best meet the needs of the strategist and decision maker.

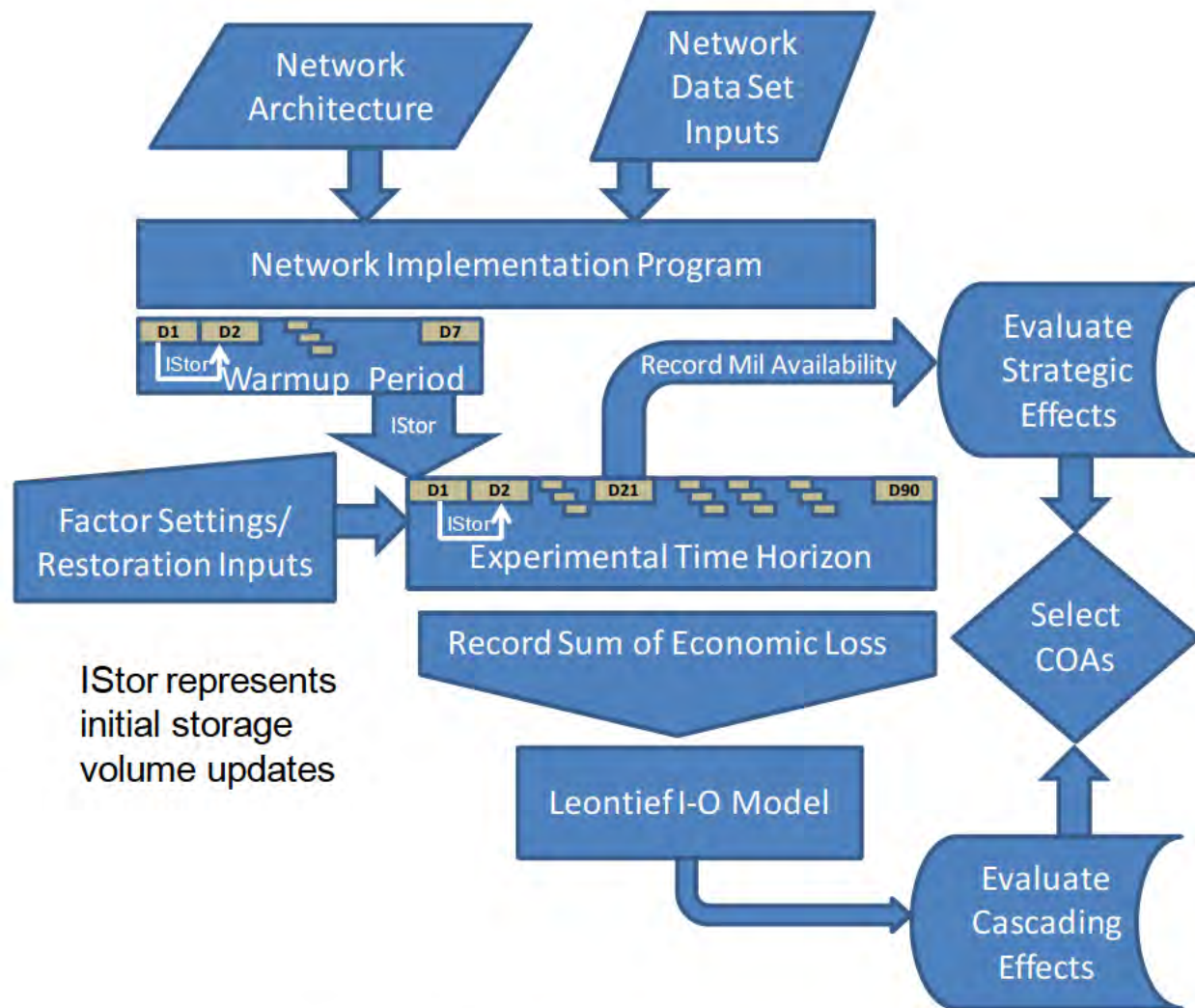


Figure 6: Flow Diagram of Solution Implementation

The implementation of this methodology will allow the modeler to gain important insights into the disruption of a petroleum supply chain in any economy of interest. A versatile computer algorithm using MATLAB 2014 implements the methodology is available in Appendix A and summarized in Table 5. This algorithm allows for the input of a network of various sizes using the constraints listed in Table 2. An analyst with a properly formatted commodity flow matrix, Input-Output matrix, and accurately aligned constraints based on a known network can input data into this network in matrix form. The automated model will

create the network effectively and collect necessary data as required. Additionally, the algorithm will implement the scenario Leontief model using the results of the network analysis. The modeler may apply interdiction or disruption parameters to any desired location, and observe the results in terms of the two defined responses, availability of military grade fuel and economic loss to the economy of interest. The results of a relevant case study using this methodology appear in Chapter 4.

Table 5: PseudoCode Algorithm for QDemand-Leontief Automated Model

Step	Description
1	Define N_K Matrix Formulation for Multi-Commodity Network
2	Set Number of products, p and supply points, i numSP
3	Build Storage Capacities, StorCap, and set initial storage, $IStor$
4	Build N multi-commodity network, AFO based on p and N_K
5	Build Demand Matrix, DemQ for each transshipment node
6	Combine AFO and DemQ into a flow equation set, FOEq and constraints, FOEqC
7	Initialize change in storage, DeltaStor, and demand shortage, SlackDem
8	Build Storage Adjustment Equation, StorAdjEq to measure changes to inventory
9	Constrain demand, DemC, and storage, StorC
10	Constrain the flow through each arc to known capacities, SumArcFO
11	Conduct Warm Up Period for d=1:D
12	Update Storage Capacity, IStor
13	Constrain Storage Capacity ,StorMax/StorMin based on IStor value
14	Update Arc Flow Constraints, UB/LBArcC
15	Update Supply Constraints, SupC
16	Format Problem for CPLEX Aeq/beq for equality coefficient and constraint matrices Aineq/bineq for inequality coefficient and constraint matrices
17	Set and constrain objective function, f using upper and lower bounds ub/lb
18	Execute CPLEX
19	Collect storage adjustment data, StorAdj for each commodity type by location
20	Recalculate initial storage levels, IStor at each iteration
21	END for loop
22	Initiate Experimental runs For e=1:E
23	Repeat steps 1-10
24	Create Beta and Exponential Distributions for Storage interdiction using a unique distribution for each disrupted node
25	Assign downtimes and recovery times for each disrupted node

26	Create Beta and Exponential Distributions for pipeline interdiction using a unique distribution for each disrupted node
27	Assign downtimes and recovery times for each disrupted arc
26	Create Beta and Exponential Distributions for refinery interdiction using a unique distribution for each disrupted refinery. Assign uniform distribution to non-military grade products as required.
27	Assign downtimes and recovery times for each disrupted refinery
29	Initialize Network Interdiction Model For $d = 1:D$
30	Update Storage Capacity, IStor
31	Apply storage interdictions to storage capacity using designed experiment, EXPMT If EXPMT(entry)>assigned node Limit Storage Capacity based on time, d >downtime End If
32	Update Storage Capacity using experiment parameters from step 31
33	Apply pipeline interdictions to arc capacity using designed experiment, EXPMT If EXPMT(entry)>assigned arc Limit Arc Flow Capacity based on time, d >downtime End If
34	Update Arc Capacity using experiment parameters from step 33
35	Apply refinery interdictions to supply capacity using designed experiment, EXPMT If EXPMT(entry)>assigned refinery Limit Refinery Capacity based on time, d >downtime End If
36	Update Refinery Capacity using experiment parameters from step 35
37	Apply import restrictions to supply capacity using designed experiment, EXPMT If EXPMT(entry)>assigned import point Limit Refinery Capacity based on time, Import Distribution End If
38	Update Import Capacity using experiment parameters from step 37
39	Repeat steps 16-20
40	Calculate Demand Shortfall by product type and calculate value of loss using price
41	Calculate daily supply of middle distillates at critical nodes, MGCrit If $d < D(\text{decisive operations})$, calculate MGCrit
42	End For
43	Initialize Leontief Model using IO Matrix, resources, and constraints
44	Set up PCDG matrix to mirror size of EXPMT x IO
45	Determine size of IO matrix, a_{ij}
46	Scale Value Loss VALLOST to time period of IO matrix
47	Set Aineq and bineq using IO and resource matrix inputs
48	Define and bound objective function, f
49	Execute CPLEX
50	Record output as a percentage of sector productivity

IV. Results and Analysis

4.1 Data Selection

The implementation of this model requires a realistic data set that represents the known production and distribution network of a country with robust petroleum refining capacity. The specific country is not critical to allow demonstration of the model. A country with a national oil company apparatus that refines, imports, and exports multiple petroleum product lines is an ideal choice. There is a variety of countries that meet the criteria, and over 80 countries worldwide possess some refinery capacity (EIA, 2007). The specific country selected for this demonstration is only a test case used for illustrative purposes, and does not indicate any possibility of conflict or other potential cause of disruption.

The purpose of this model demonstration is to show how the model produces useful results using appropriately assigned parameters and factors within the network and associated experiment. The method of interdiction is not a focus and the model is intended to support any type of attack where network restoration will occur. While this experiment focuses on restoration distributions specified in the methodology, the user may select any appropriate distribution package. Additionally, this demonstrative scenario focuses on minimizing cascading and collateral effects on the impacted economy while still achieving acceptable levels of strategic success against military fuel supplies. Users of this model might choose to exacerbate cascading effects, and similar experimentation methods could also inform appropriate interdiction strategies for that goal. The modeler and strategist are left to determine which factors, critical geography, time horizons, interdiction levels, and distributions are most appropriate based on their adversary and concept of operations. Because this demonstration is

notional, any adjustment to its implementation parameters or data sets in subsequent studies is wholly appropriate.

Many unclassified sources exist that provide substantial data on refinery networks and their capacities. The Organization for Petroleum Exporting Countries (OPEC) maintains a database of supply, demand, and infrastructure data including refined petroleum and other related industries for all of its member countries. OPEC publishes this information annually in its statistical yearbook (“OPEC Annual Statistical Bulletin, 2013). The Department of Energy of the United States and many other countries provide detailed data of the national and global energy markets with specific analysis related to refined petroleum (EIA, 2014). Some national oil companies are publicly traded and release detailed information regarding their production of refined products and the associated distribution network. The national oil company of Mexico, PEMEX, is one such organization. PEMEX publishes a statistical yearbook annually (“PEMEX Statistical Yearbook, 2003-2013,” 2014).

Additionally, there is a detailed supply data available from the Mexican Secretary of Energy (SENER) that includes delivery data of refined petroleum products to every distribution hub within the country of Mexico and other key information regarding the distribution network (SENER, 2014). For these reasons, Mexico is an appropriate choice for an illustrative test case that will validate the model and provide insight into the impacts of an interdiction.

Based on data from PEMEX and the Mexican Secretary of Energy, the model requires information essential to the development of a realistic case study of a refined petroleum production and distribution network. The essential data components collected from SENER include refinery locations and output levels, storage locations with consumption quantities and import capabilities. PEMEX provided a schematic of the distribution network with pipeline

routes and data regarding end user prices and refinery specific data. SENER provided a much higher level of disaggregation for production levels, and this data proved useful to populate the refinery network and distribution facilities.

The production network includes 6 refinery locations with the maximum capacity determined using the monthly production levels observed over the most recent 12 month period. Additionally, four known import locations are assigned a maximum capacity based on 40% of product consumption that is imported (EIA, 2014). Using information provided by SENER to populate the model, distribution points receive shipments and satisfy a known local demand for each transshipment node. As per the aggregate model assumptions, this demand represents the daily average for the most recent 12 month period. Fixed demand is also necessary to feed the input-output model that operates on an assumption of short term stability. Known fuel oil consumption by petroleum-fired electrical power plants located throughout Mexico augments the fuel oil demand component of the data set (GEO, 2014).

The storage capacity of each transshipment node was not available in the data. This gap was alleviated through the use of equation (3.11). A safety stock factor, inaccessible lower storage bound, and initial storage quantities are populated in the model using reasonable estimates from the data set (Miesner and Leffler, 2006: 290-291). Although these values are subject to significant adjustment based on the known parameters of an individual network, they are fixed throughout the experimental implementation.

4.2 Case Study Network Development

Using PEMEX data, the geography of the network is established through the creation of an incidence matrix. This N_K matrix includes 10 supply points and 76 pipeline arcs across the column entries, and 75 distribution nodes including refinery supply points in the row entries.

The incidence matrix is formulated for each of four product lines including gasoline, diesel, kerosene, and fuel oil. The incidence matrix is the essential component of the $Q*Dem$ model that provides the flow balance at the transshipment nodes for each product line in equation (7)-(9). This product is too large to allow visual representation in this document.

In the test case problem, six locations are selected based on historical actions and bases of operation from the Mexican campaign of 1846-47 as depicted in the West Point Atlas series shown in Figure 7 (“Mexican War Overview Map,” 2014). While the concept of operations from the Mexican War is strategically obsolete, similar selection criteria should feed the planning process that determines the location of critical supply points. The application of planning priorities by an operations staff will enable the analyst to select and prioritize these locations to best support decisive operations.



Figure 7: Concept of Operation for Selection of Critical Locations (WP Atlas Series)

In order to demonstrate the effectiveness of a selective surgical strike, the illustrative experimentation plan interdicts six of the 76 network distribution nodes and associated facilities in the indicated region. This plan establishes target regions within the historical example and takes into account the limited availability of strike capacity, planning resources, and funds available to allow a combatant commander to complete a strategic interdiction.

For each of the six critical points, there are six associated pipelines and six transshipment or storage locations in the modern distribution network. Additionally, each of these pipelines is serviced by the most proximate refinery and point of importation. Pipeline, storage, refinery, and import locations are all vulnerable to disruption. The interdictor could potentially target any or all of these vulnerabilities using a variety of means.

In order to limit the number of design points to a combinatorial factor that focuses the decision space, vulnerable points are rank ordered by their criticality to the network and by limiting redundancy. For this example the criticality assignments are based on geographical distance from a point of embarkation with the point of enemy resupply (4) given greater consideration. There are six pipeline connections and storage locations that are vulnerable. There are three proximate refinery locations and importation points that service the six critical nodes. In every case, the interdictor can decide to take no action. The resulting design requires two factors with seven possible factor levels and two factors with four possible factor levels. JMP software creates a randomized design for each experiment to ensure that run order does not impact the results. This design includes four replicates at each setting. Each experimental design analysis description includes a snapshot of the design utilized to implement the model best suited to test each hypothesis. The network geography represented in the incidence matrix is displayed in Figure 8: Petroleum Network Schematic.

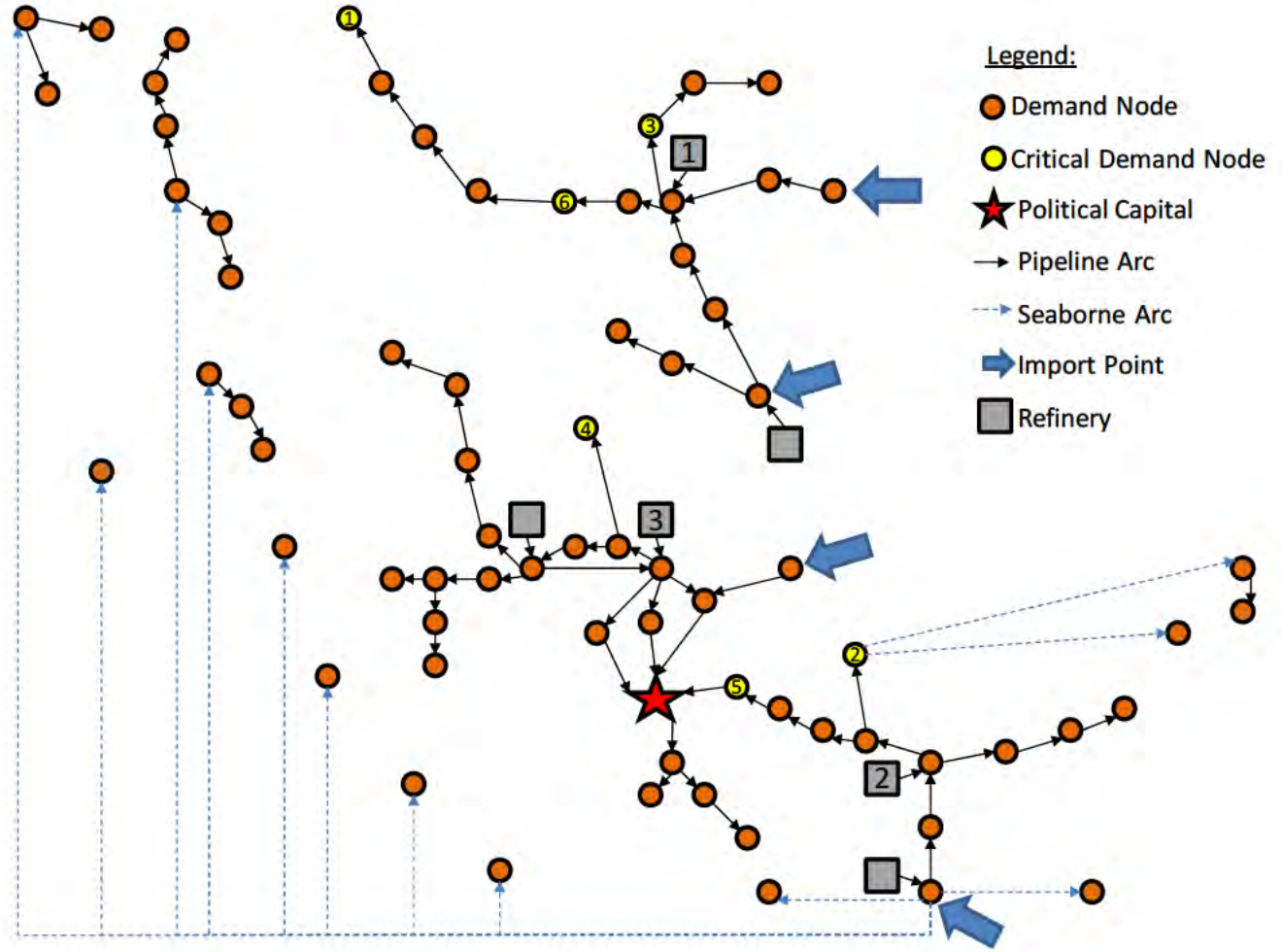


Figure 8: Petroleum Network Schematic

There are four types of decision variables that populate the model from Table 2. These include the daily quantity of each product type shipped between each network node.

Additionally, the weighing factor that powers the maximization function is populated and the value of $Q_{j,p}$ is bounded between -1 and 2. This creates the ability of a transshipment node to receive up to two days worth of supply at a time (distribution of which is split between daily demand and storage) and ship up to one day worth of supplies to a subsequent location. The bounds of $Q_{j,p}$ can be adjusted as necessary to model the expected actions of an adversary. The

weights, $w_{j,p}$, that accompany $Q_{j,p}$ are selected using critical locations of conflict and resupply from the Mexican campaign of 1846-47 (“Mexican War Overview Map,” 2014).

Once the network model is fully populated with the data set, the Q^*Dem model is implemented using the CPLEX solver. The full model using the illustrative test case data set as described in Table 2 requires 1352 constraints and 1244 decision variables. An initial implementation of 7 days models the network immediately preceding a planned interdiction. This time period is characterized by the network manager optimizing shipments to critical distribution nodes in order to maximize supplies available prior to an anticipated interdiction. The analyst can vary this time period accordingly based upon the known time lapse between the manager’s anticipation of a disruption and its actual occurrence. The output from this initialization provides a more accurate assessment of the initial storage volume of petroleum products at each distribution hub.

The construction of an input-output matrix for a national economy can be a vast undertaking as described by Haimes *et al.* (2005). The data requirements include commodity purchases and highly specific production numbers for all sectors of industry that are included in the model. Many agencies publish input-output matrices for various regional and state economies including the Organization for Economic Cooperation and Development (OECD, 2014). The publication by OECD is suitable for use in problem methodology, although it has aggregated the petroleum products industry. The OECD data includes most major industries including those encompassing critical infrastructure such as transportation, medical care, agriculture, utilities, and government services. A summary of this Input-Output Matrix for the country of Mexico as provided by OECD is included in Table 6 (OECD, 2014). The full IO Matrix is attached in Appendix B. An essential characteristic of this I-O Matrix is the

requirement that Industry Output (last column in Table 6) and Total Industry Outlay (last row in Table 6) summations are identical in order to ensure flow balance within the Leontief model.

This calculation is an augmentation to the original OECD statistics.

Table 6: IO Matrix of Select Industries for the Country of Mexico, Pre-2010 (OECD, 2014)

Variable		Total													
Period		Period Pre 2010													
Currency		Millions of Mexican Pesos													
Column Sector		Agriculture	Mining and quarrying	Refined petroleum	Chemicals	Electricity and Utilities	Transport	Finance	Government and defence	Healthcare	Total Intermediate Consumption	Households Consumption	Government Consumption	Exports EXPO	Industry Output
Row Sector	i														
Agriculture		50573	2	11	1795	2	3	0	4	10	269664	181911	0	35372	513263
Mining and quarrying		106	7672	158712	88475	3914	32	3	6	5	303836	467	0	183649	551305
Refined petroleum		7062	4332	2316	5999	16822	65071	18	4744	1198	159395	74406	0	15748	275483
Chemicals		18214	20111	12414	78689	37212	6713	43	4376	19327	363036	145157	1	48025	615518
Electricity and Utilities		5028	2897	313	3605	32594	4341	834	7432	3541	152750	84141	0	882.48	238864
Transport		8609	5532	1620	9518	8921	24159	1683	4905	3125	217328	522741	0	55550	816336
Finance		5731	12378	1482	4227	4314	24761	38307	8839	461	195458	93423	30058	12574	331513
Government and defence		0	0	0	0	1278	3222	1199	0	0	5759	4263	412665	0	422688
Healthcare		12	7	3	17	11	28	12	11	11	461	131595	161936	104.54	294315
Total Imports		59499	10853	32930	211888	103	12048	24409	0	0	1957592
Total Intermediate consumption /final use at basic prices		172364	100237	201356	268856	142357	289142	117171	104681	73079	5219776	4770674	1161789	2E+06	5219776
Taxes, less subsidies, on products		1799	1013	639	1781	2614	16131	-51	938	423	42526	351640	0	0	42526
VALU Value added at basic prices		279601	439202	40559	132993	93789	499015	189984	317068	220812	7162773				7123399
GOPS Gross		229272	148860	23305	83816	57847	329079	126227	1930	92839	4487421				
LABR Compensation of Employees		50212	34663	17206	47150	35314	169454	59461	312765	127348	2370474				
OTXS Other taxes, less subsidies, on production		116	255679	48	2028	628	481	4296	2373	625	304878				
PROD Gross output (Production) at basic prices		453763	540452	242553	403630	238760	804288	307104	422688	294315	12425075				
Total industry outlay		513263	551305	275483	615518	238864	816336	331513	422688	294315					

A method for disaggregation of industries within an A matrix is presented by Gibbons, Wolsky, and Tolley (1982) using parameters to minimize the error inherent from aggregation. This methodology provides a means of taking an aggregated industry such as refined petroleum products, and decomposing into components such as gasoline, kerosene, naphtha, and diesel (Gibbons, Wolsky, and Tolley 1982). While the uses of each type of petroleum product within an industry is readily available from data provided by the Energy Secretariat of Mexico, these

petroleum types are produced and distributed using common processes, equipment, labor pools, and logistical networks (SENER, 2014). Although the decomposition of specific commodity applications within various dependent industries is widely documented, it would not be valid to disaggregate the amount of inputs required from other industries to produce each measure of diesel, gasoline, kerosene, and so forth. For example, since most refined petroleum liquids are derived from nearly indistinguishable crude stocks and undergo similar distillation processing that consumes multiple inputs, there is no reliable methodology to determine what percentage of each input is responsible for rendering a unit of final petroleum product (Inkpen and Moffit, 2011 445). These inputs are assigned to the petroleum refinement process, which is appropriately represented as the inputs necessary to produce the complete pool of refined petroleum products.

4.3 Experiment Introduction

The experiments conducted using the notional case study include four scenarios and associated experiment sets. Significance is determined using a t -statistic provided by JMP11 software with a default 95% confidence setting and a value of $\alpha=.05$ for all reported results. The responses tested in each experiment include the availability of fuel summed across critical nodes between the interdiction and the commencement of decisive operations, defined in the scenario as 21 days. Additionally, the daily demand shortages at all nodes are summed across the entire 90 day model run in order to inform the analysis of cascading effects. The responses are collected using a script that collects summations of the appropriate variables for each day of the 90 day interval of the model. For the lost value, the model sums the unmet demand for every location and product. Independent daily storage volumes are available for all supply nodes within this automated model, and the user may choose to collect measurements of specific point

volume fluctuations in support of an applied strategic problem. The script prices this shortfall using data available from SENER (2014) regarding the value of a barrel of each product, summarized in Table 7. The model in question uses 2010 fuel price data to provide consistency with the input output data in Table 6 with consideration of price volatility. The duration of decisive action and the planning horizon can be set at any level; the 21 and 90 day respective time horizons used for this illustrative analysis are subject to alteration by the analyst.

Table 7: Cost (Pesos) of a Barrel (42 US Gallons) of Various Fuel Types (SENER, 2014)

Product Type/	Year	Cost (Mex\$/BBL)	
		2006	2010
Pemex Magna gasoline		1057.19	1307.94
Pemex Diesel		862.54	1357.19
Jet fuel		1001.27	1342.85
Heavy fuel oil		517.96	975.11

4.4 Experiment 1: Supply Interdiction Scenario

This initial experiment is intended to test hypothesis 1, which investigates whether supply interdiction is insufficient to deplete military fuel availability or inflict economic losses. Experiment 1 will also inform the analysis of cascading effects by determining the value of economic losses in the targeted economy. The test includes experimentation with all six refinery locations within the PEMEX production system as well as four prominent importation points as indicated in Figure 8. The factors for this experiment include the number of refinery interdictions and the number of importation points subjected to embargo strategy. The refinery factor requires seven levels ranging from a scenario of no interdictions as the lowest level (0) through six interdictions as the highest level (6). The factor for embargo of import points includes four levels ranging from no interdictions (Level 0) to three interdictions (Level 3).

These are discrete settings for this experiment, as the decision to interdict a location is binary. Variation is introduced by the random variable generated by the distributions representing the duration of the disruption.

Replicating the experiment four times requires 112 model runs to explore the entire decision space, which required 19 minutes and 20 seconds using an AMD Athlon II X2 215 2.7 GHz Processor. An abbreviated example of the first ten entries of this randomized matrix with the documented results, produced in JMP11 is presented in Table 8 and labeled with factor levels 1-7 for refinery interdictions and levels 1-4 for importation interdiction. The storage and arc factor setting columns are placeholders that are set at zero in this experiment but will be populated in later scenarios. Note that the pipeline importation point in Figure 8 is considered diplomatically constrained based on the scenario and is therefore not interdicted.

Table 8: Randomized Factor Level Settings for Supply Experiment Design (Abbreviated)

FACTOR LEVEL SETTING				RECORDED RESPONSE	
Refinery	Storage	Arc	Import	Value Lost (Pesos)	Military Availability (CBBL)
0	5	3	0	15183842284	12734.76
0	4	4	0	15438669726	10054.89
0	2	5	0	16155368056	14906.43
0	4	6	0	17757671235	8281.85
0	7	6	0	16856543420	8632.29
0	5	4	0	15021808894	13579.09
0	5	1	0	13230360279	20919.69
0	7	5	0	16187837742	5900.63
0	4	7	0	18054943991	7016.49
0	3	4	0	15266244775	16811.18

The refineries and import points are rated by their proximity to the critical nodes, and this informs the order in which the factor level implements an interdiction of a specific facility. The

ordering is in accordance with the labels in Figure 8 for both refineries and importation points. The system is allowed a 7 day warm up period that models the network manager's efforts to maximize storage capacity at critical nodes within the network. This warm up period is implemented by allowing the script in Appendix A to run for 7 daily iterations without interdiction using a weighting scheme consistent with the interdiction modeling phase. Each of the 112 model runs is implemented using the MATLAB script in Appendix A by using the randomized matrix of the model runs with each replicate as shown in Table 8. As each replicate of the model runs to completion, the responses are recorded appropriately as shown in columns 5 and 6 of Table 8.

The results are tested using consistent distribution parameters to inform the restoration timeline. Initial restoration periods (25% capacity) for this experiment use a minimum initial downtime for disrupted refineries of 10 days, most likely of 21 days, and maximum of 30 days to inform the β distribution as defined in equation (22)-(25). These inputs replicate historical norms described by the US Department of Energy (EIA, 2007). An exponential distribution derived from the β -distribution output determines the time lapse for additional restoration of resources using increments of 25%. Importation effectiveness is modeled across a uniform distribution with limits specified between 75% and 90% effectiveness. The high level of effectiveness results from the dependence on seaborne imports within this economy. Tanker ships are historically vulnerable to embargo demands due to risk aversion within the shipping industry that is inherent to their significant expense (Inkpen and Moffett, 2011: 416). Importation disruptions remain effective throughout the conduct of operations that cease after 60 days.

The initial investigation tests the significance of importation and refinery production on military availability at the onset of operations, set at 21 days from the interdiction. The results of the experiment of the effects of supply interdictions on the availability of military grade fuel appear in Figure 9. The resulting empirical models and t -statistic results appear in Table 9. The information in Table 9 required a screening feature in JMP11 that identifies significant factors, second order effects, and interactions. The screening feature produces a half-normal plot that identifies which effects are most appropriate for the model. The results confirm that importation is not significant to military availability as evident in the red highlighted t -statistic indicating that the importation factor does not significantly contribute to the model. The model results confirm hypothesis $H_{1.1}$ and supports the conclusion that an import embargo will not significantly affect military fuel availability within this case study. Figure 9 shows the actual output of the model run against the prediction based on the empirical model produced in equation (29). This figure provides a snapshot of the predictive power of this empirical model denoted by the distance between the predicted values on the horizontal axis and actual results on the vertical axis. This graph shows the ability of the empirical model to estimate the behavior of the system and is summarized by the ANOVA chart in Table 9 and the R -squared predicted value of .76. This model is reasonably accurate, but probably insufficient because of its reliance on only two significant effects that include refinery settings and their second-order effects. Imports, while included in the model represented in Table 9, do not significantly contribute to the estimates.

It is important to note that the scenario is quite limited in scope for an embargo scenario. While refinery interdictions necessarily occur briefly before decisive operations because of their often kinetic nature, sanctions and embargo strategies may remain in place months or years ahead of military actions. However, the ability of the network manager to prioritize military

facilities amongst recipients of domestic refinery products would still enable an adversary to stockpile fuel resources within in a limited period of time. This result best represents a military action such as a blockade of ports prior to a military intervention.

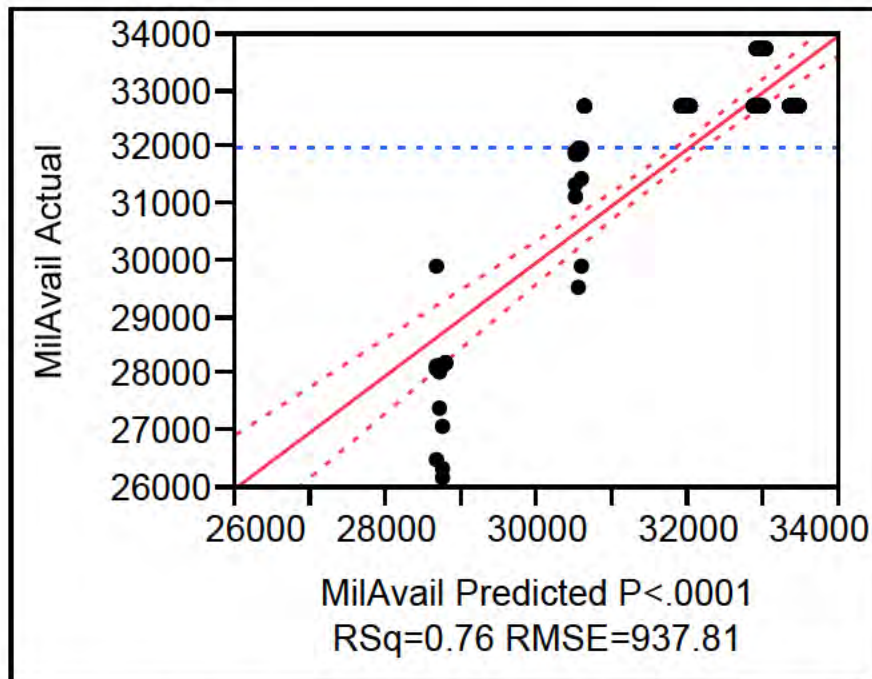


Figure 9: Military Availability Model Predictive Capability for Supply Interdiction

However, refinery supply does have a significant impact on military fuel availability as shown in Table 9 and highlighted in green. We therefore reject hypothesis $H_{1,1}$ for refinery supply and accept its alternative: refinery supply interdiction factors and second-order effects significantly impact the availability of military grade fuels at critical supply locations.

Table 9: Statistical Analysis of Supply Interdiction Impact on Military Availability**Analysis of Variance**

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	3	296492755	98830918	112.3730
Error	108	94984924	879490.03	Prob > F
C. Total	111	391477679		<.0001*

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob> t
Intercept	35856.36	298.32	120.19	<.0001*
Refinery	-708.92	44.30	-16.00	<.0001*
Import	-35.70	79.25	-0.45	0.6532
(Refinery-4)*(Refinery-4)	-230.09	25.58	-8.99	<.0001*

Because importation does not significantly impact the availability of military supplies at critical nodes for this scenario and time horizon, a streamlined empirical model can adequately represent the system without including importation as a factor. This model uses the parameter estimates from Table 9 after removing the Import factor and is represented in equation (29). In accordance with the hypothesis test convention, Z_1 represents the supply factor settings and Z_1^2 accounts for the quadratic effects. This empirical model includes an intercept and these two terms that show significance in the half-normal plot and statistical analysis.

$$\hat{y} = 35856.36 - 708.92 Z_1 - 230.09 Z_1^2 \quad (29)$$

Because the interdiction of importation does not significantly impact military availability, the expected fuel availability summed at critical nodes in the scenario prior to decisive operations is influenced in this experiment by the level of disruption of refinery operations. Hypothesis $H_{4.1}$ is accepted for importation factors, which do not demonstrate statistically significant effects on the availability of military grade fuels at critical supply locations. Refinery operations have a significant impact and inform the model in Equation (29) that

provides reasonably effective predictive power demonstrated by the R-squared adjusted statistic of .76 that determines the level of correlation.

As evident in Figure 10, the increase in the number of refineries interdicted has an increasing negative effect on military fuel availability as the system becomes incapable of providing sufficient supply at those locations. However, even with complete interdiction, these critical nodes still have access to over 80% of their maximum levels of supply due to their storage inventory as evident in Figure 10. This result indicates that while statistically significant, a refinery interdiction does not sufficiently hamper military availability in a manner that is likely to operationally impede the ability of an adversary to conduct operations during the time horizon. This test only considered availability at 6 critical node locations, which is less than 8% of total storage facilities. There is sufficient military grade fuel stored throughout the system to weather a supply interdiction and maintain a robust stock level at critical nodes. In conclusion, neither type of interdiction proved capable of substantially depleting the military grade fuel supplies at critical node locations to a magnitude that a combatant commander might find acceptable for a short campaign. This alternative is not sufficiently effective as a stand-alone strategy within the boundaries of this case study and is unlikely to inform an acceptable military course of action under these circumstances.

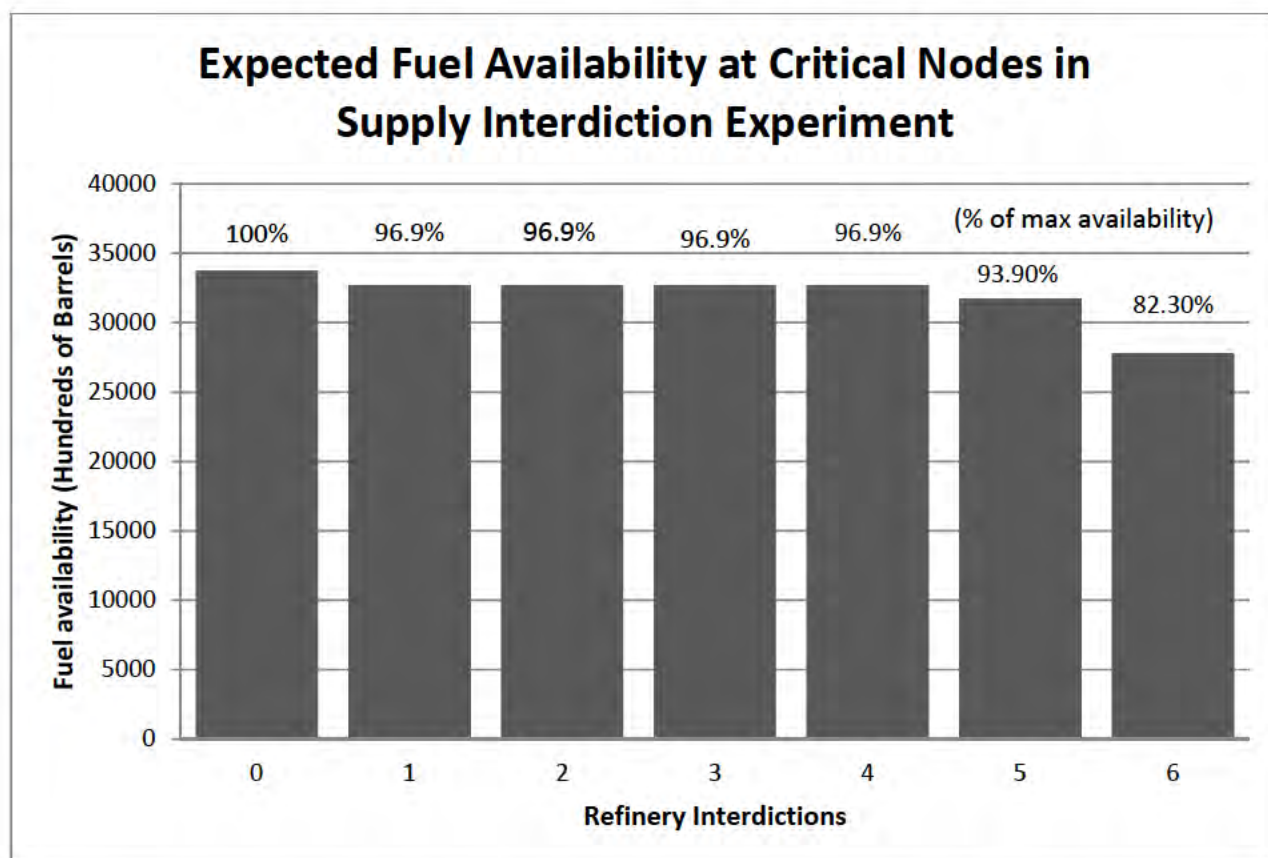


Figure 10: Military Fuel Availability at Increasing Refinery Interdiction Levels

Using similar statistical procedures in JMP11, the regression analysis presents experimental results measuring the economic value of the total unmet demand during the duration of the experiment (90 days). The results of the statistical analysis are presented in Figure 11. This model shows excellent predictive power with an R-squared adjusted statistic of 85% and consistent analysis of variance results.

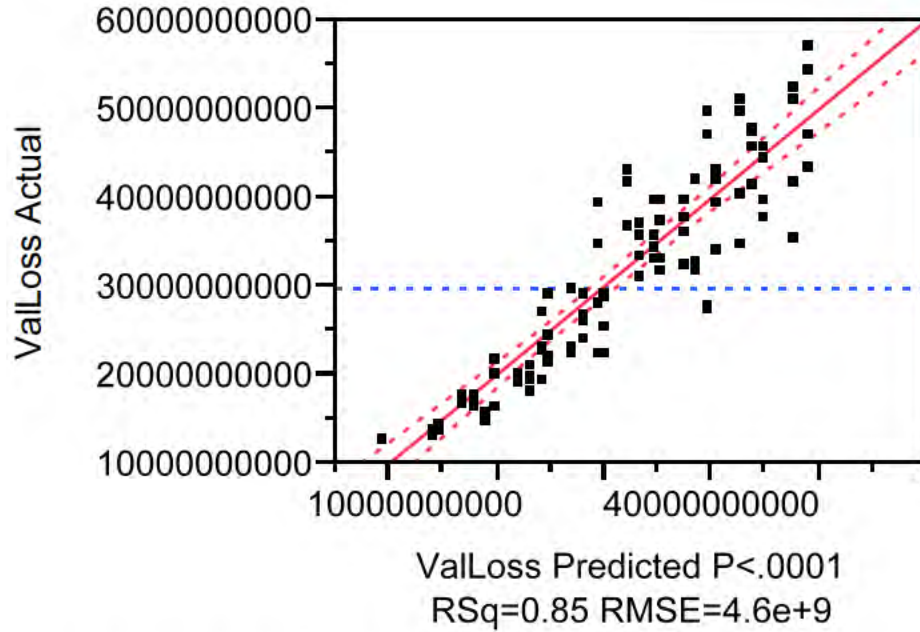


Figure 11: Economic Value Losses Model Predictive Power

The analysis presented in Table 10 shows that the t -statistics for factors of refinery and importation interdiction levels (highlighted in green) are statistically significant. This assessment results in the empirical model presented in equation (30). This empirical model is simply a reformulation of the parameter estimates shown in Table 10, with the factor inputs represented as β terms. Based on this assessment, hypothesis $H_{1,2}$ is rejected for both refinery and importation factors. This result leads to the conclusion that supply interdictions of both types will significantly impact the measurable economic loss based on unmet demand as stated in alternative hypothesis $H_{1,2A}$. There are no statistically significant interactions or second order-effects in this model.

Table 10: Statistical Results of Supply Interdiction on Value of Economic Losses**Summary of Fit**

RSquare	0.853715
RSquare Adj	0.849652
Root Mean Square Error	4.567e+9
Mean of Response	2.97e+10
Observations (or Sum Wgts)	112

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	3	1.3148e+22	4.383e+21	210.0949
Error	108	2.253e+21	2.086e+19	Prob > F
C. Total	111	1.5401e+22		<.0001*

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob> t
Intercept	3.075e+9	1.468e+9	2.10	0.0385*
Refinery	5.1658e+9	2.158e+8	23.94	<.0001*
Import	2.8195e+9	3.86e+8	7.30	<.0001*

Codifying the significant factors leads to the empirical model in equation (30), which represents the expected economic loss at different factor settings of refinery (Z_1) and importation (Z_2) interdiction. Replacing Z_1 with the number of refinery interdictions and Z_2 with the number of importation disruptions within equation (30) would result in an estimate of the value of economic loss inflicted by the solution. This model would remain valid for any factor setting using the same model parameters.

$$\hat{y} = 3.075e+9 + 5.1658e+9 Z_1 + 2.8195e+9 Z_2 \quad (30)$$

The implementation of equation (30) leads to the response surface presented in Figure 12, which graphically depicts the behavior of economic losses across a range of factor level settings

for refinery and import interdictions. As expected, the highest levels of refinery and import interdiction settings will inflict the most substantial amounts of economic loss within the petroleum industry. However, refinery interdiction inflicts economic losses at a much more severe rate than import restrictions alone. This is evident in the significant slope of increasing value losses along the refinery axis in Figure 12. Using the empirical model that is developed from the experimental design, refinery disruptions impact economic losses at over three times the rate as do importation restrictions when each is considered independently. This surface shows a decision space that provides insight to an operational planner regarding the impacts of economic loss at various factor settings.

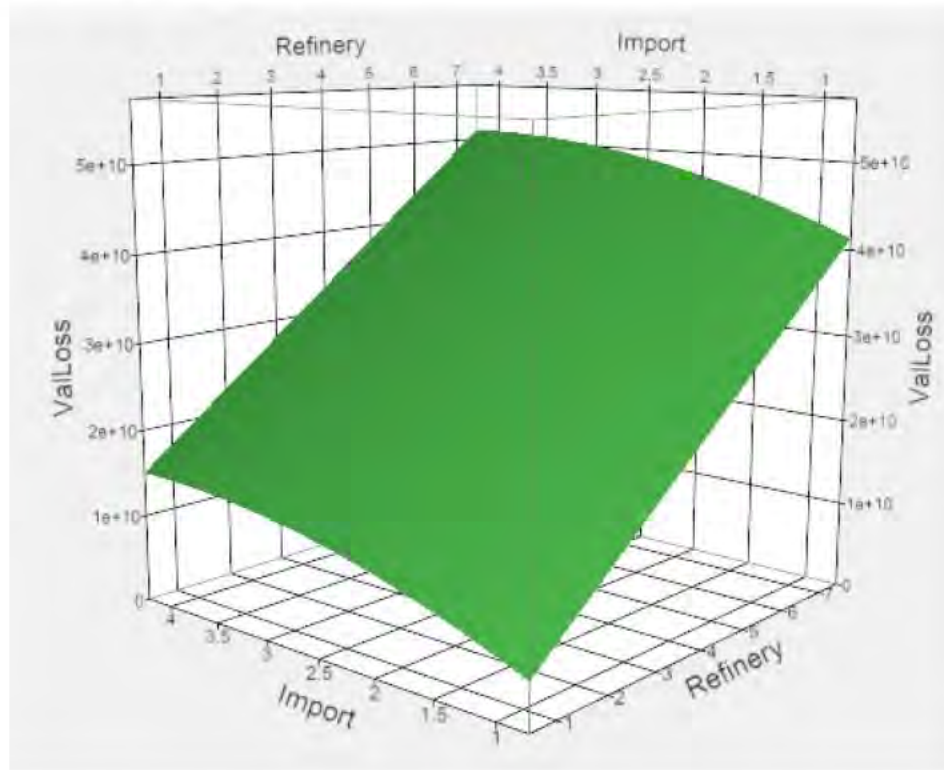


Figure 12: Response Surface of Value of Economic Loss Response to Supply Interdictions

This empirical representation is intended to capture the surface produced using the actual experimental results represented in Figure 13. The experimental results indicate the mean of the

value losses for each factor setting across four replications. Since this model is implemented discretely, the results in Figure 13 show how the system responded to different variations of interdiction strategy against the supply assets in the order specified within Figure 8. The modeler can determine what relative levels of detriment are realized to the local economy using these outputs. As evident in these results, the coupling of supply and importation restrictions can have a severe impact on the value of losses to the economy and will inform the degree of cascading effects. A spike is evident at 3 refinery interdictions which results from the size of the facilities at that factor setting. Investigation of this raw data enables the validation of a practical impact to the economy based on statistically significant factors.

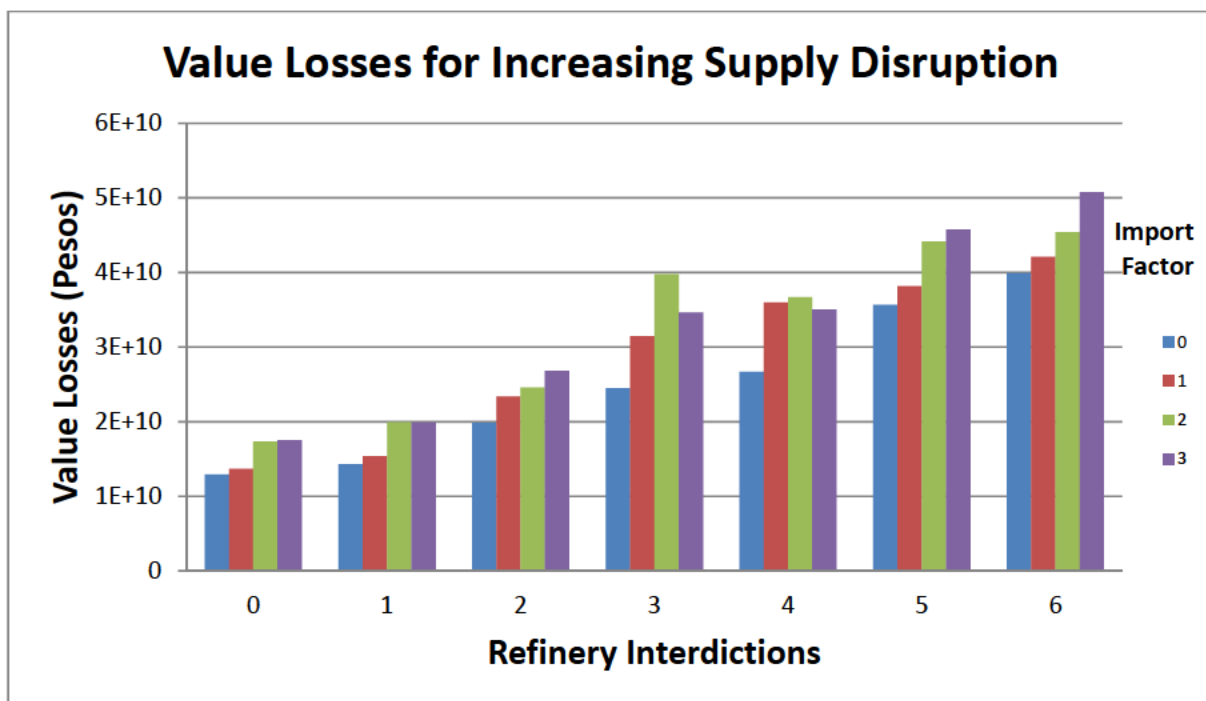


Figure 13: Economic Value Losses for Increasing Factor Levels of Supply Interdiction

Assessing the results in Figure 13 using the Leontief model implementation requires inputting the results of the value lost by removing the sum from the refined petroleum sector of the economy represented in Table 6. The resulting assessment of the reduced value of the

refined petroleum sector updates the constraint, X_i^* in accordance with equation (21).

Constraining the economic input of petroleum products available to the economy will then cascade through the economic model using the formulation implemented in equation (19).

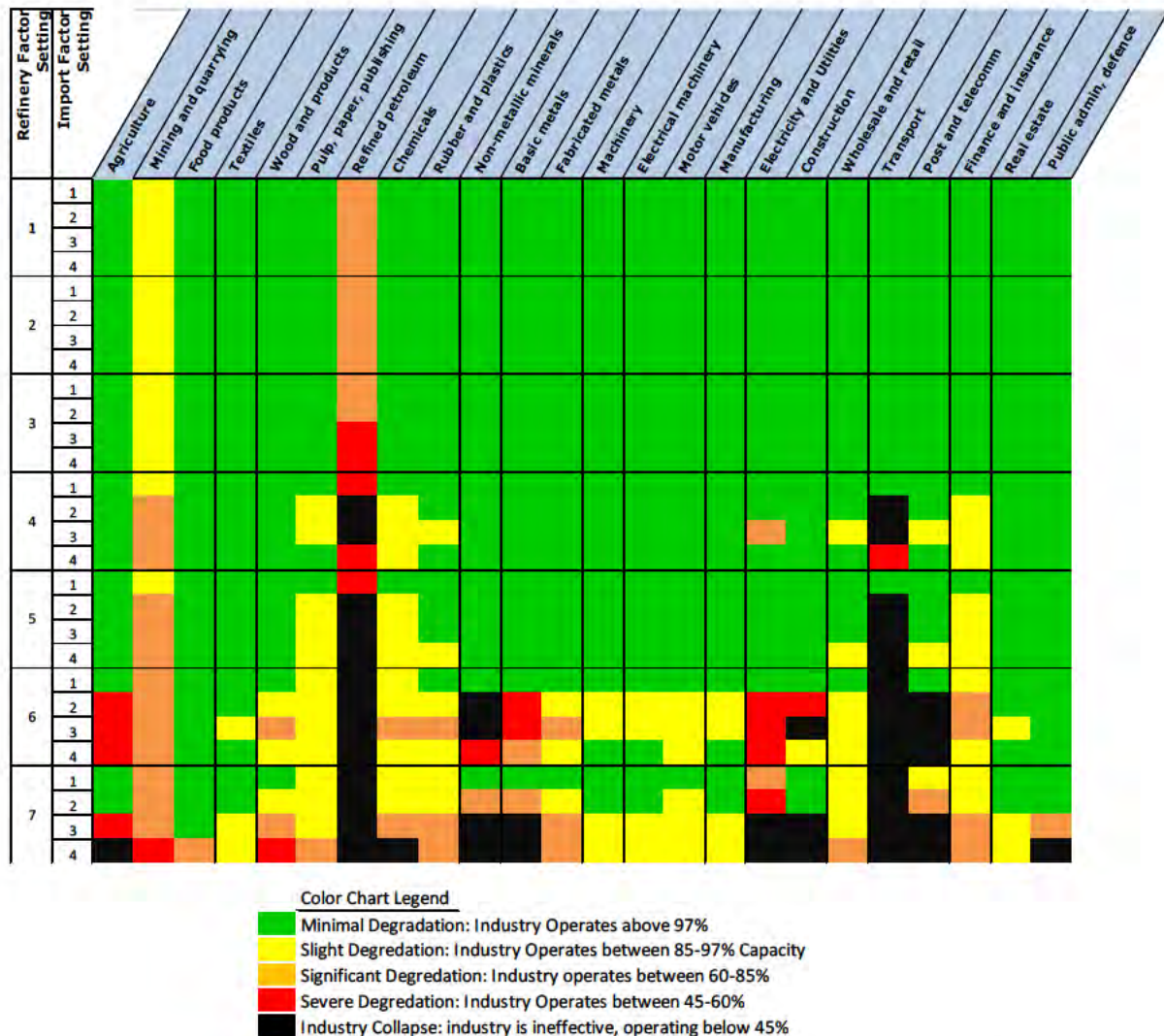
The effects of this cascading is presented in Table 11, which shows several critical industries and the impact of the cascading effects expected for various factor level settings. The results use data collected from the value of economic loss in the supply interdiction experiment. This analysis is assessed consistently throughout the results. The t -statistic applied to each of the four sample points, n is shown in equation (31). This lower bound allows the analyst to state that 95% confidence in the conclusion that the resulting cascading effects will be no worse than the analytical outcome.

$$LBCI = \bar{x} - tinv(.05, n)s / \sqrt{n} \quad (31)$$

The color key in Table 11 specifies various levels of degradation within each industries at the indicated factor level combinations. Within the selected economy, mining and transportation are at particularly high risk due to their reliance on refined petroleum as a buyer or provider of resources, respectively. Other key industries such as agriculture, materials production, and finance begin to suffer increasing effects due to their relation to these activities. In general, this economy proves relatively robust to all but the highest levels of supply interdiction, indicating that the economy is not overly dependent of fossil fuels for the duration of the time horizon. Some industries, such as textile and food production do not appear to suffer significant degradation despite extreme interdiction of petroleum product supplies. Most courses of action considered in this scenario would allow for this economy to maintain a basic level of function. Complete interdiction of the supply network is necessary to severely disrupt the economy as long as the petroleum network management can implement reasonable efforts to restore capacity

while storing sufficient fuel reserves within the available infrastructure. The impact of limiting restoration activity is considered in Experiment 3.

Table 11: Cascading Effects of Supply Interdiction in Select Industries



In conclusion, interdiction of supply resources within the specified economy did not cause significant cascading effects at anything but the highest levels of disruption for the planning horizon and storage quantities. This economy proved robust to interdictions of supply, even with up to 75% of petroleum product value removed from the economy. However, the use of supply interdictions without consideration of the distribution network and its storage

capacities did not provide a substantial reduction in military grade fuel supplies available to the end user at critical locations over the 21 day timeframe for decisive operations. Depending on the goals of the decision maker for an interdiction force, supply interdiction alone is not likely a sufficient solution to achieve a military or political end state within this economy.

4.5 Experiment 2: Network Interdiction Experiment

The objective of this experiment is to test hypothesis 2, which determines if network interdiction can effectively deplete military fuel availability or significantly impact economic losses. Additionally, the experiment will ascertain the cascading effects on the targeted economy by analyzing the measured value of economic losses over the time horizon. The test includes experimentation with six storage locations and polyducts within the PEMEX distribution system that services the critical nodes highlighted in Figure 8. The factors for this experiment include the number of storage facility interdictions and the number of polyduct disruptions. Both factors require seven levels ranging from a scenario of no interdictions as the lowest level (0) through six interdictions as the highest level (6). These are discrete settings for this experiment, as the decision to interdict a storage facility or pipeline is binary. However, the degree of the interdiction allows consideration of the factor settings as continuous functions. Variation is introduced by the random variable generated by the distributions representing the duration of the disruption or the speed with which a network manager can implement alternative solutions to the network outage.

Replicating the experiment four times requires 196 model runs to explore the entire decision space, which required 34 minutes and 41 seconds using an AMD Athlon II X2 215 2.7 GHz Processor. An abbreviated example of the first ten entries of this randomized matrix with the documented results produced in JMP11 is presented in Table 12. The labels correspond with

factor levels 1-7 for storage interdictions and levels 1-7 for pipeline interdictions. The factor levels are scaled from a value of one, which represents the baseline of zero interdictions through 7 representing the maximum of 6 interdictions. The Refinery and Import setting columns are placeholders that are set at zero in this experiment.

Table 12: Randomized Factor Settings for Network Experiment Design (10 Replicates)

Refinery	# of Storage Sites	# of Arc Pipelines	Import	Value of Losses (Pesos)	Military Availability (CBBL)
0	5	3	0	15183842284	12734.77
0	4	4	0	15438669726	10054.90
0	2	5	0	16155368056	14906.43
0	4	6	0	17757671235	8281.85
0	7	6	0	16856543420	8632.29
0	5	4	0	15021808894	13579.09
0	5	1	0	13230360279	20919.69
0	7	5	0	16187837742	5900.63
0	4	7	0	18054943991	7016.49
0	3	4	0	15266244775	16811.19

The pipelines and storage facilities are rated by their impact to critical nodes; this informs the order in which the factor level implements an interdiction of a specific facility. The ordering is in accordance with the labels in Figure 8 for both pipelines and storage facilities. The system is again allowed a 7 day warm up period similar to Experiment 1 using a weighting scheme for $Q_{j,p}$ consistent with the interdiction modeling phase. Each of the 196 model runs is implemented using the MATLAB script in Appendix A. This script assigns factors based on the randomized matrix of the model runs with each replicate as shown in Table 12. As each replicate of the model runs to completion, the responses are recorded appropriately as shown in columns 5 and 6 of Table 12.

The results are tested using consistent distribution parameters to inform the restoration timeline. Initial pipeline restoration periods (33% capacity) for this experiment use a minimum (a) initial downtime of 4 days, most likely (b) of 7, and maximum (c) of 14 days to inform the PERT analysis and β distribution as defined in equation (25). This distribution is intended to replicate the full range of options for restoration of commodity flow by the network manager. This could include restoration of the pipeline, patching the disrupted section of the polyduct, or reliance on other means of product delivery such as rail or truck transport.

Initial storage facility restoration periods (33% capacity) for this experiment use a minimum initial downtime of 7 days, most likely of 14, and maximum of 30 days to inform the β distribution as defined in Equation (25). The distribution allows restoration of 1/3 of the original storage capacity after this initial downtime period. This distribution is intended to replicate the full range of options for restoration of storage capacity by the network manager. This could include repair of the facility, implementation of temporary storage vessels such as tanker trailers or blivets, or reliance on other means of product delivery such as rail or truck transport (Trench, 2001: 3). An exponential distribution derived from the β parameter output determines the time lapse for additional restoration of resources using increments of 33.3% for both types of network architecture.

The initial results using the raw data produce an estimate of the reductions in military grade fuel availability given increasing levels of network interdiction. These levels indicate the degree to which higher numbers of interdictions on storage and pipeline facilities within the scenario will deny fuel stocks to critical locations. The results of the raw experimentation are presented in Figure 14. These results are promising because they show a significant level of depletion of fuel availability with a limited number of storage interdictions. For example,

disrupting four storage locations that are proximate to the critical nodes resulted in a loss of over 50% of military grade fuel availability in every course of action. Disabling all of the storage locations resulted in a 75% reduction in four of the seven potential courses of action.

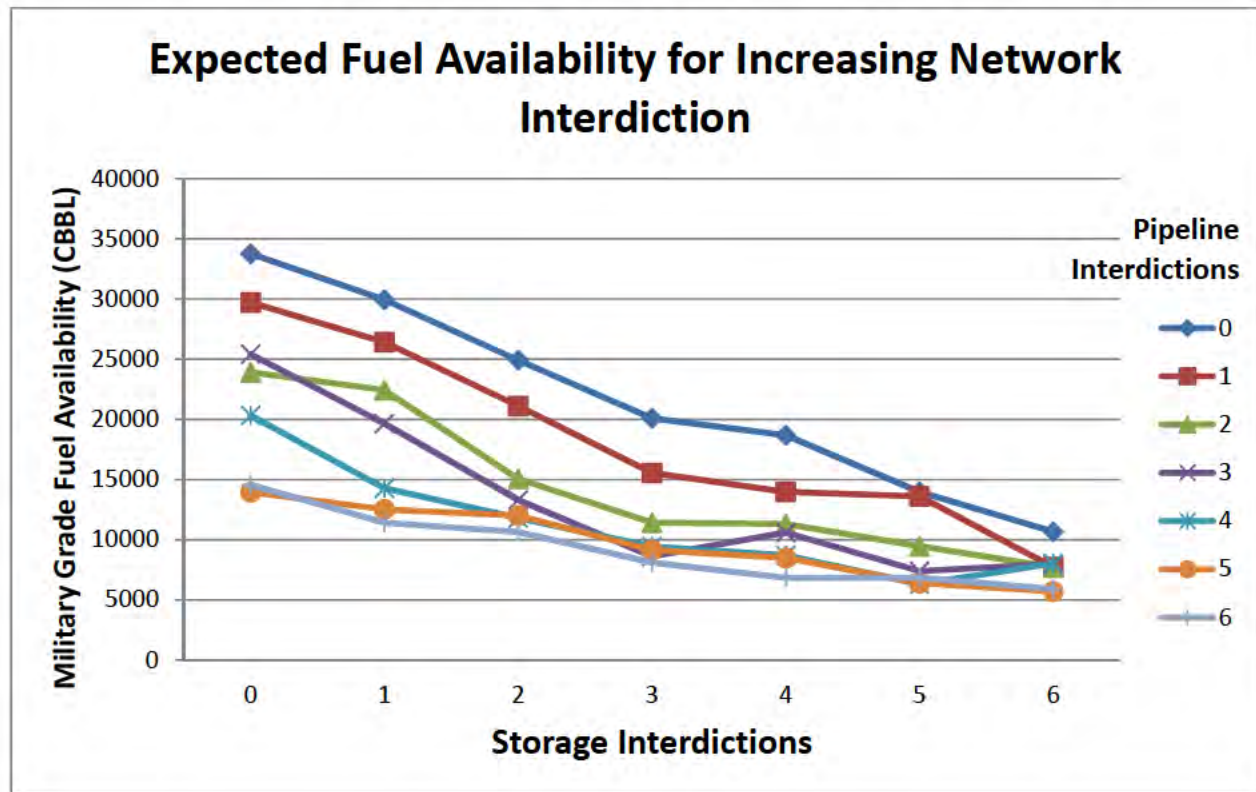


Figure 14: Expected Military Grade Fuel Availability for Network Interdiction Factors

This experiment tests the significance of network disruption on military availability at the onset of operations, set at 21 days from the interdiction. The statistical results of the experiment of the effects of network interdictions on the military availability of fuel are shown in Figure 15. Figure 15 shows the actual output of the model run against the prediction based on the empirical model produced in equation (32). This figure provides a snapshot of the predictive power of this empirical model denoted by the distance between the prediction and the actual results.

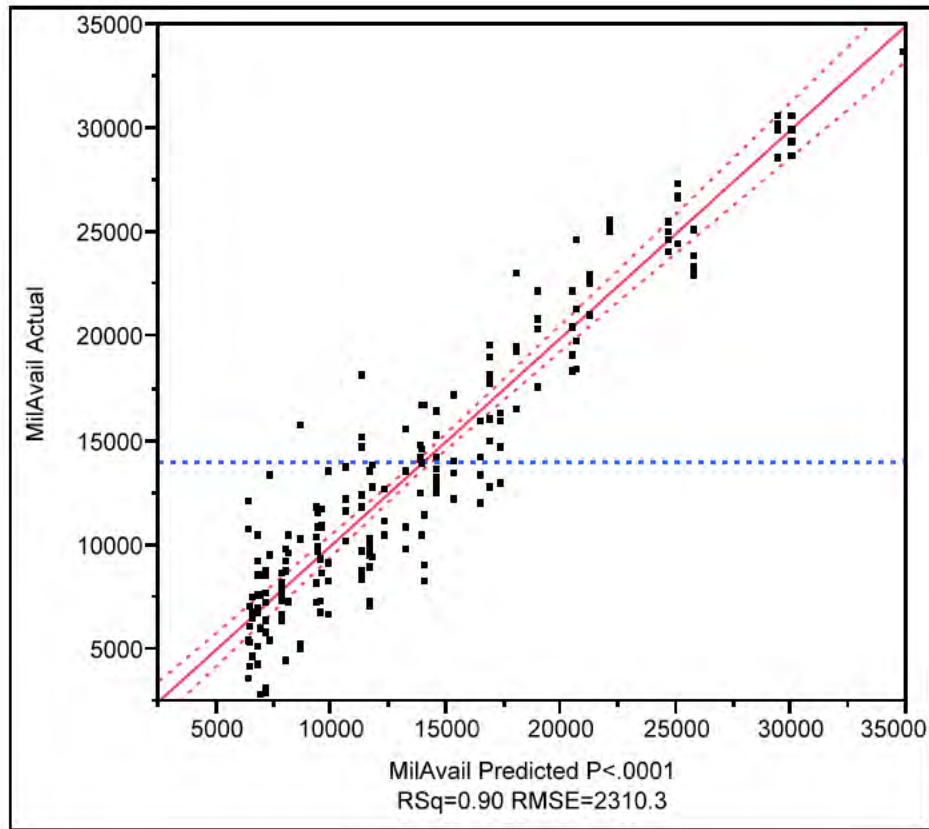


Figure 15: Military Availability Model Predictive Capability for Network Interdiction

The resulting empirical models and t -statistic results are shown in Table 13. Table 13 is produced using a screening feature in JMP11 that identifies significant factors, second-order effects, and interactions using a half-normal plot. The results confirm that network interdiction of storage and pipeline infrastructure significantly impacts military availability as evident in the green highlighted t -statistic in Table 13. This result also confirms multiple significant factors, interactions, and second order (squared parameter terms) that significantly contribute to the disruption of the petroleum availability.

The experiment results support rejection of hypothesis $H_{2,1}$ and acceptance of the alternative conclusion, $H_{2,1A}$; a network interdiction will significantly affect military fuel

availability within this case study. This conclusion is valid for both storage interdiction and pipeline disruption courses of action within this scenario.

Table 13: Statistical Analysis of Supply Interdiction Impact on Military Availability

Summary of Fit

RSquare	0.903227
RSquare Adj	0.90068
Root Mean Square Error	2310.276
Mean of Response	14001
Observations (or Sum Wgts)	196

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	5	9465085787	1.893e+9	354.67
Error	190	1014101112	5337374.30	Prob > F
C. Total	195	1.0479e+10		<.0001*

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob> t
Intercept	30045.81	563.6496	53.31	<.0001*
Arc	-2545.82	82.50	-30.85	<.0001*
Storage	-2067.55	82.50	-25.06	<.0001*
(Arc-4)*(Arc-4)	314.44	47.63	6.60	<.0001*
(Arc-4)*(Storage-4)	439.26	41.25	10.65	<.0001*
(Storage-4)*(Storage-4)	287.73	47.63	6.04	<.0001*

As evident in Table 13, pipeline and storage interdiction factors, the interaction term, and both second order interactions contribute significantly to the model. The statistical significance of these factors suggests a predictive model as a response surface that augments the empirical solution presented in equation (32). This empirical model uses Z_3 to represent storage factors and Z_4 to represent pipeline factors and accommodate their interactions and second-order effects.

$$\hat{y} = 30045.81 - 2545.82*Z_4 - 2067.55*Z_3 + 314.44*Z_4^2 + 439.26*Z_4*Z_3 + 287.73*Z_3^2 \quad (32)$$

The response surface developed in JMP11 using the Gaussian process tool is presented in Figure 16. The model shows how varying levels of network interdictions will impact the availability of military grade fuel at critical locations across the model run. The response surface indicates that increasing levels of storage and pipeline interdiction will impact the military availability in a similar manner. A strategy that combines these interdiction factors shows significant potential as an effective strategy to interdict the delivery of military grade fuels. The benefit of an applicable response surface is that higher order effects are effectively captured to show what region of the decision space is most applicable to achieve the end state of the decision maker while considering potential operational constraints. It is notable that this process could also utilize a discrete classification for factor settings. Although the behavior is most certainly continuous because of potential changes in the impacts of an interdiction, the decision to interdict a particular target is binary in nature. This analysis could instead utilize a step function response surface, but the smoothed function shown in Figure 16 is more readily interpreted. Additionally, a discrete response surface would still require curvature at the edges of each setting in order to produce a coherent surface.

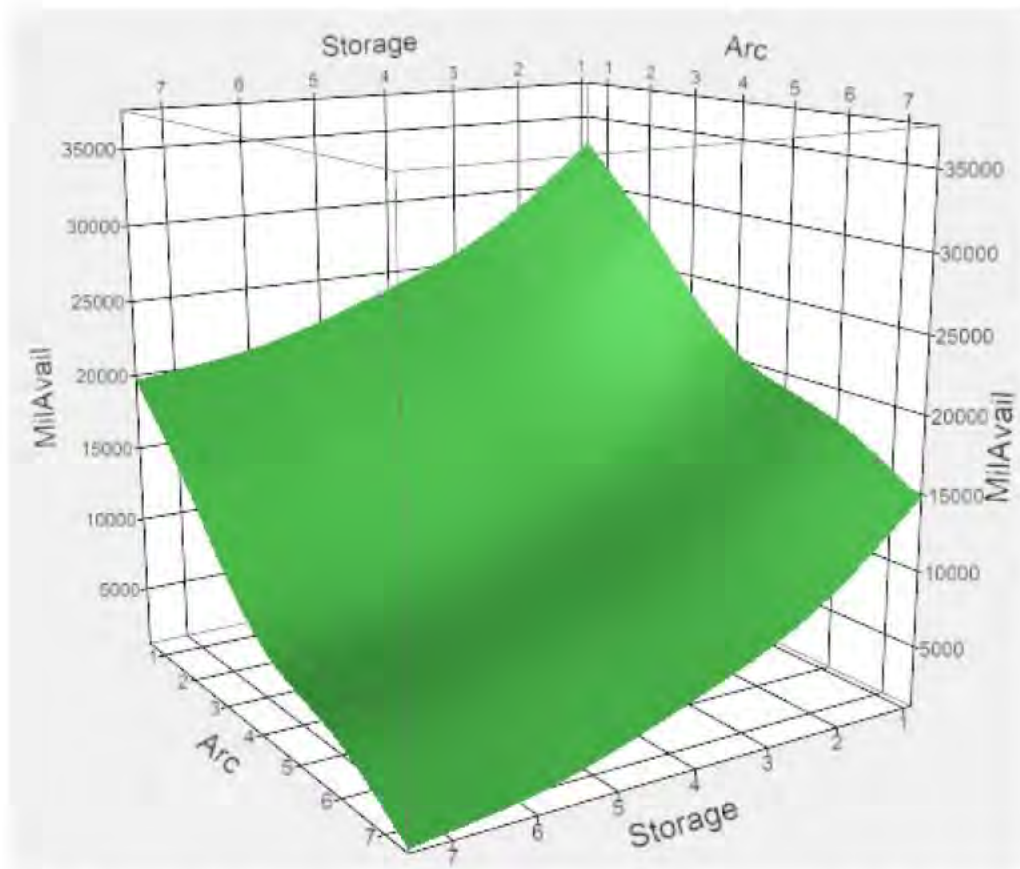


Figure 16: Response Surface of Interdiction Impact on Military Grade Fuel Availability

After reapplying the screening tools in JMP11, the regression output presents experimental results measuring the economic value of the total unmet demand during the 90 daily iterations of the network interdiction for experiment 2. The results of the statistical analysis are presented in Figure 17, which shows the fitted model against a ‘data cloud’ collected from the experiment. This model shows reasonable predictive power with an *R*-squared adjusted statistic of .81 and acceptable results for analysis of variance. This analysis shows several outliers generated by the experiment that are highlighted in red within Figure 17. Removal of these points did not substantially change the model and their presence accounts for less than two percent of the 196 model runs. The use of an exponential distribution for subsequent recovery

times produced these outliers. Future uses of this experiment might limit the length of downtimes or utilize a more precise distribution to limit the occurrence of these outliers. However, in an actual interdiction, the analyst could expect vast differences in the time required to restore different network disruption locations due to the severity, risk, and resources available to the network manager.

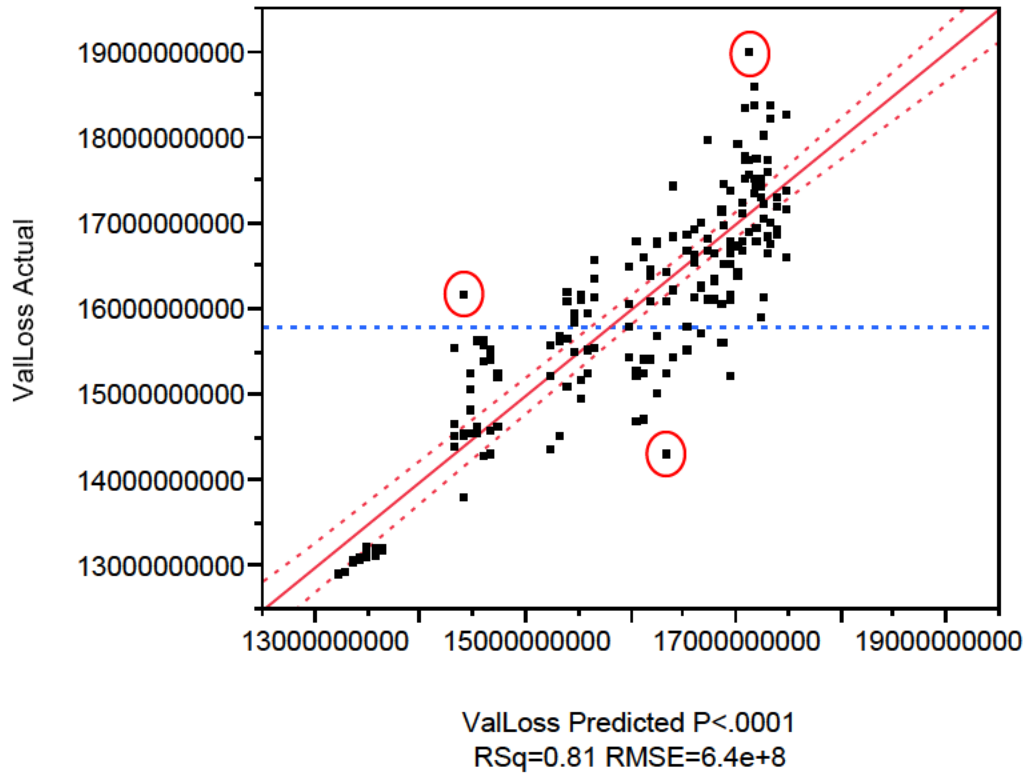


Figure 17: Statistical Analysis of Network Interdiction Impacts on Value of Economic Loss

The analysis presented in Table 14 shows that the t -statistics for factors of arc, storage and arc quadratic factors (highlighted green) are statistically significant to the value of economic loss. Additionally, the second order component for pipeline interdiction is significant (green highlight). This assessment results in the empirical model presented in equation (30). Based on this assessment, hypothesis $H_{2.2}$ is rejected for both refinery and importation factors. This result

leads to the conclusion that $H_{2.2A}$ is accepted; network interdictions of pipelines and storage facilities will significantly impact the value of economic loss created by unmet demand.

Table 14: Statistical Analysis of Network Interdiction Impacts on Economic Losses

Summary of Fit

RSquare	0.814524
RSquare Adj	0.811626
Root Mean Square Error	6.396e+8
Mean of Response	1.58e+10
Observations (or Sum Wgts)	196

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	3	3.4492e+20	1.15e+20	281.0586
Error	192	7.8541e+19	4.091e+17	Prob > F
C. Total	195	4.2346e+20		<.0001*

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob> t
Intercept	1.334e+10	1.469e+8	90.83	<.0001*
Arc	639106318	22842308	27.98	<.0001*
Storage	69294350	22842308	3.03	0.0028*
(Arc-4)*(Arc-4)	-94315403	13188013	-7.15	<.0001*

In the interdiction experiment, the result of the impact on the value of economic losses is very similar between the experimental results and the empirical model. As observed in Figure 18, the affect on the value of economic loss at increasing levels of storage and pipeline interdiction is modest. While there are modest improvements, the test indicates that the network manager loses more value from their prioritization scheme than is created by the network interdiction. The network optimization process allows the allocation of fuel storage capacity to critical locations at the expense of other storage locations. This results in economic losses based on unmet demand resulting from prioritization strategies rather than interdiction. The effect of this prioritization on the value of economic loss is apparent in Figure 18 because the setting of

zero pipeline and arc interdictions does not result in a zero value for economic losses. These economic losses are a result of the prioritization strategy that requires the networks to limit distribution to non-critical demand locations in order to build critical storage capacity. The trends are mirrored in the empirical data on the left and the raw data graphic on the right of Figure 18. Since the manager anticipates and response to an interdiction based on maintaining supply at critical locations, other nodes in the system will experience shortfalls based on the implementation of the Q-Demand maximum flow optimization. This policy is effective in maintaining supply inventories at the critical locations for as long as possible but at the cost of increased economic losses elsewhere in the system. If the analyst determines that this scheme is not realistic, the value of $Q_{j,p}$ requires a minimum value of one to ensure that each supply node continues to receive shipments capable of replenishing daily demand for as long as possible within the time horizon.

Although the three factors highlighted in Table 14 indicated significant impacts based on the t -statistic, Figure 18 shows very limited practical impact within the scenario and time horizon. Despite the conclusions of the hypothesis, we can observe that network interdiction results in a less economic impact on the economy represented in the case study than was found in the supply scenario. The contribution of storage is the most severely limited despite its statistically significant contribution. Figure 18 shows the relationship between the empirical representation of the experimental results on the left and the raw data graph on the right. These representations of the results clearly support the power of the empirical model. Additionally, the limited impact of network interdiction on economic loss is highlighted by the limited response adjustments as factor levels increase.

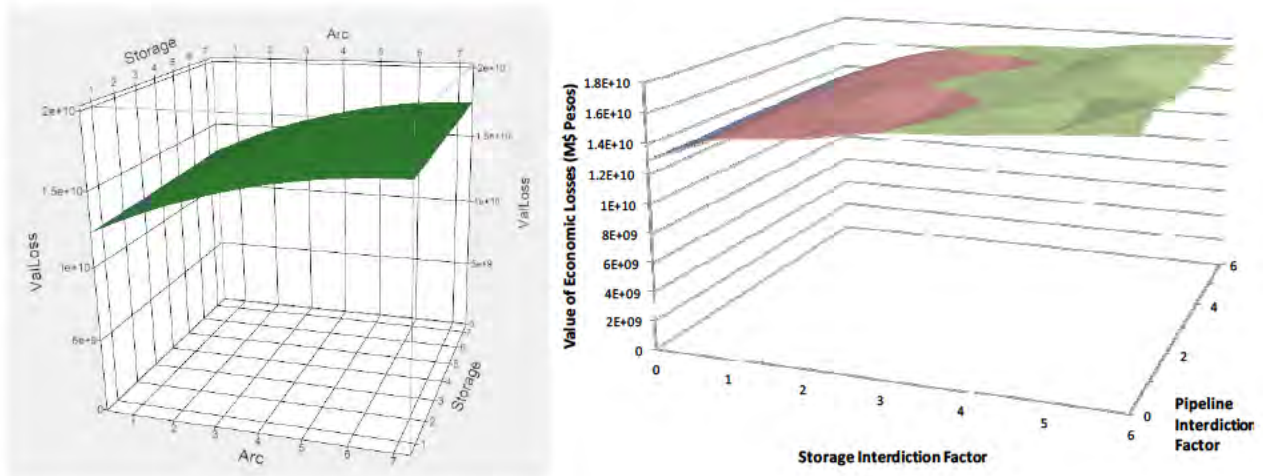


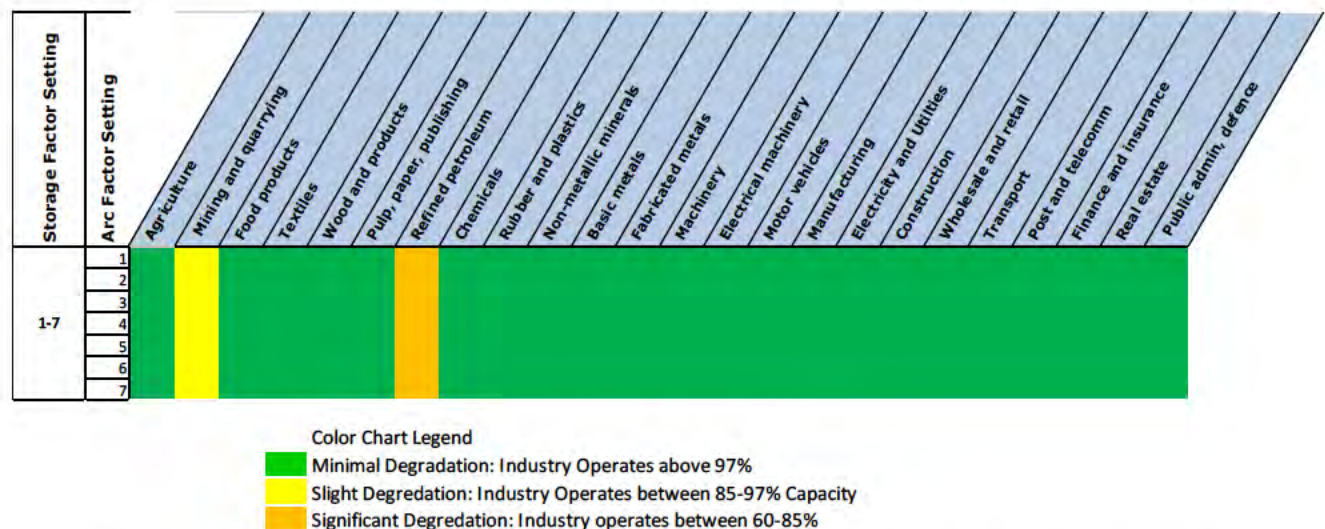
Figure 18: Comparison of Representations of NW Interdiction on Economic Losses

Assessing the results in Figure 18 with the Leontief model implementation uses the estimate of the value lost by removing the sum from the refined petroleum sector of the economy as described in Experiment 1. Since the measured economic losses are lower than experiment 1, limited cascading impacts are expected in this iteration.

The cascading effects resulting from shortfalls in demand are presented in Table 15. This graphic shows a range of critical industries and the impact of the cascading effects expected. The color key specifies where these industries meet various levels of degradation. Within the selected economy, mining is the only industry with a measureable degradation in effectiveness during the time horizon. Given the limited time period and the restricted areas of operation, the experiment result might be expected. This economy proves highly resilient to all levels of network interdiction for the time horizon. The result shows that the disruption of a limited portion of the network architecture is not sufficient to substantially impact this economy over the course of the 90-day model. While there is some loss to the mining industry as a result of limits on crude demand, no other industry shows a significant decrease in operating capacity at any combination of factor level settings. The impact of disrupting 6 network pipelines over the

course of a 90-day model would have supported a reasonable prediction of a greater level of cascading effects. The speed of the pipeline restoration (minimum of 4 days), short measurement of time intervals, and the geographical selection of the pipeline interdictions may have played a role. For example, no pipeline section that directly services a metropolis was included in the model. Additionally, the storage interdictions only affected a small portion of total facilities as previously described.

Table 15: Cascading Impacts of Network Interdiction in Select Industries



The interdiction of network infrastructure shows a versatile ability to deny petroleum product supplies to an adversary while limiting the cascading effects within the remainder of the economy. A commander interested in limiting the damage to the local economy using this specific scenario could chose from courses of action that impact storage and transport facilities in the critical areas. By denying the ability to move and store fuel, this strategy would provide dramatic and immediate effects on the battlefield and limit effects to the remainder of the economy. Unlike supply interdiction strategies in the previous scenario, these actions only

impact limited areas within the economy and lack the widespread shortages that would instigate catastrophic cascading effects.

4.6 Experiment 3: Supply and Network Interdiction

Experiment 3 uses a combination of significant factors from experiments 1 and 2 in order to test Hypothesis 3. The results of experiment 3 will determine what combinations of known significant factors are best suited to an effective interdiction strategy. Additionally, combinations of these factors and their interactions will inform a characterization of expected cascading effects determined using the value of economic losses measured within the experiment.

Experiments 1 and 2 revealed that storage, pipeline, and refinery interdiction had significant impacts on the availability of military grade fuel at the critical node locations. The disruption of imports did not cause a significant decrease in the availability of military grade fuel. Additionally, there was no statistically significant interaction with refinery interdiction to indicate a contribution to military availability. Therefore, it is not a viable military strategy against this particular economy under the parameters for this scenario because the resulting humanitarian impacts are without military justification. The analyst may consider a lengthened time period of import point disruption if appropriate given the strategic constraints for their problem set.

Removing import points as factors in the experiment leaves three remaining factors. In order to limit the decision space in this experiment, the refineries considered for interdiction are limited to three locations with proximate location to a critical demand node. This leaves four factors for refineries and the original seven factors settings for pipeline and storage point interdiction defined in experiment 2. Implementing this experiment with four replications

requires 784 model runs to explore the entire discrete design space. Using an AMD Athlon II X2 215 2.7 GHz Processor, the time required for the experiment is 2 hours, 18 minutes. A summary of the first ten randomized replications is included in Table 16.

Table 16: Randomized Factor Setting Levels for Complete Experiment Design

FACTOR LEVEL SETTING				RECORDED RESPONSE	
Refinery	Storage Sites	# Arc Pipelines	Import	Value Lost (Pesos)	Military Availability (CBBL)
3	2	4	0	33269332862	11802.37
3	6	5	0	34477725935	176.32
1	4	1	0	13014515488	16801.75
4	3	5	0	46181058721	1855.17
4	3	6	0	44031366545	1855.17
4	1	3	0	43453564457	20501.95
3	3	3	0	32319770178	7866.47
2	6	1	0	17498255253	2923.20
4	2	4	0	44778071161	11802.37
3	3	7	0	36250861902	1898.33

4.6.1 Single Strike

The experiment includes two different scenarios that warrant further investigation. The first scenario is similar to experiments 1 and 2, which use a β Distribution to determine the length of initial network outages. The interdictor conducts a single strike package allowing the adversary to begin recovery immediately. This model allows restoration using the same inputs previously described for experiments 1 and 2. Restoration times for all factors result from a β -distribution generated by a random stream using PERT assumptions with appropriate settings for pipelines ($a=4$, $b=7$, $c=14$), refineries ($a=10$, $b=21$, $c=31$), and storage facilities ($a=7$, $b=14$, $c=30$). This scenario will determine the dynamics of the system when the network manager is

permitted the opportunity to restore network capacity in a timeframe that is consistent with historical norms (“Refinery Outages,” EIA, 2007).

4.6.2 Re-strike

The second scenario will assume that the interdictor has a re-strike capability that can debilitate targeted infrastructure and render it completely incapacitated until the onset of decisive operations. This time horizon remains set at 21 days as in other experiments. After the 21 day re-strike interdiction strategy runs its course, the network restoration process in this scenario will begin using the same process previously used in the first scenario or previous experiments. Throughout this section, results analysis will include both scenarios and a comparison of the alternatives

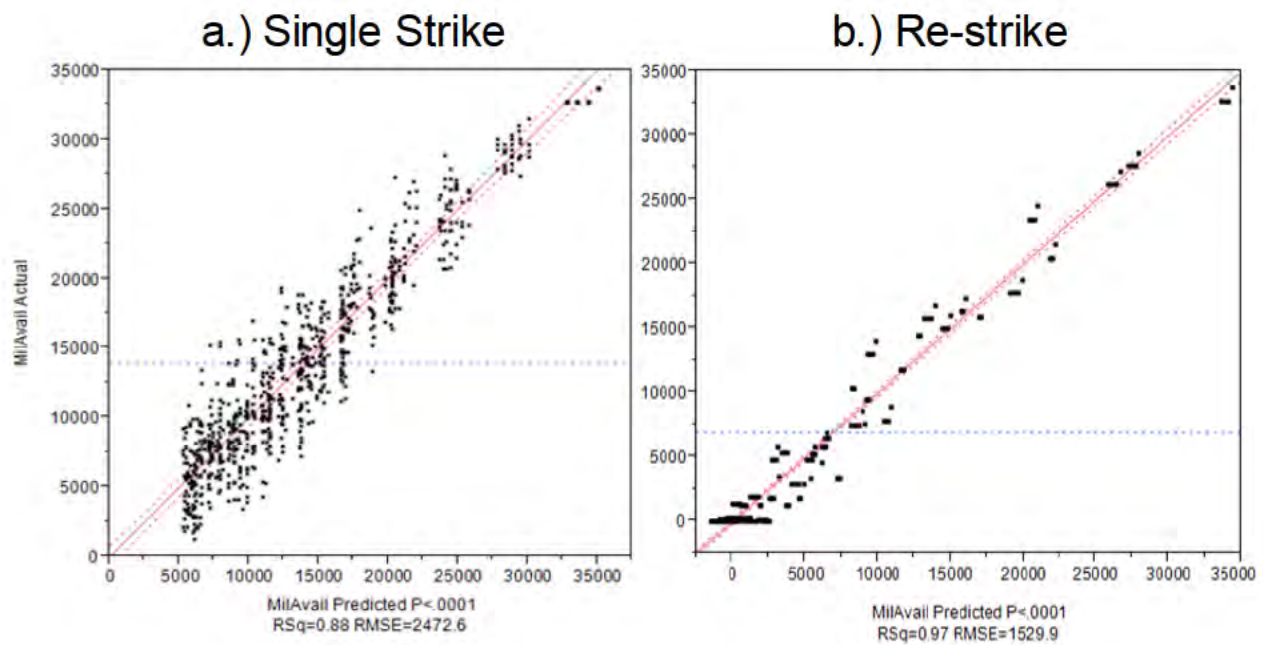


Figure 19: Statistical Comparison of Single Strike and Re-strike Empirical Model for Supply and Network Interdiction

4.6.3 Supply and Network Experiment Results

Because the re-strike scenario constrains the time period over which restoration might occur, the associated results show a much lower occurrence of variance and produce an empirical model of substantial predictive power and limited variance. This result is evident in the re-strike fitted model shown to the right in Figure 19. The results for both models in Figure 19 indicate a well-fitted empirical representation that adequately captures the experimental results. The re-strike scenario has improved predictive power indicated by its *R*-squared adjusted value of greater than 97%. This advantage is due to the reduction in variance induced by limiting the time period of restoration.

Table 17: Statistical Comparison of Single Strike and Re-strike Scenarios

		Scenario				
Summary of Fit	Single Strike	Restrike				
	0.881855	0.97101				
	0.880789	0.970673				
	2489.79	1470.31				
	13917.43	6932.35				
	784	784				
Analysis of Variance						
Source	DF	SS	MS	F Ratio	Prob > F	
Single Strike						
Model	7	3.59E+10	5.13E+09	827.4539	<.0001	
Error	776	4810471310	6199061			
C. Total	783	4.07E+10				
Restrike						
Model	9	5.60E+10	6.23E+09	2880.507	<.0001	
Error	774	1673247474	2161818.4			
C. Total	783	5.77E+10				
Parameter	Estimate	Std Error	t Ratio	Prob> t	SS	F Ratio
Single Strike						
Intercept	29715.76	363.02	81.86	<.0001		
Arc	-2490.82	44.46	-56.02	<.0001	1.95E+10	3138.60
Storage	-2068.52	44.46	-46.52	<.0001	1.34E+10	2164.56
Refinery	-17.89	79.53	-0.22	0.8221	313636.6	0.05
Arc*Arc	296.85	25.66	11.56	<.0001	8.29E+08	133.73
Arc*Storage	307.18	22.23	13.82	<.0001	1.18E+09	190.94
Storage*Storage	324.09	25.66	12.63	<.0001	9.88E+08	159.40
Arc*Refinery	87.77	39.76	2.21	0.0276	30202490	4.87
Restrike						
Intercept	24042.01	246.29	97.61	<.0001		
Storage	-2837.08	40.10	-70.74	<.0001	1.08E+10	5004.07
Arc	-2210.98	26.25	-84.21	<.0001	1.53E+10	7091.32
Refinery	-50.51	46.96	-1.08	0.2825	2500646	1.15
Storage*Storage	450.20	15.15	29.7	<.0001	1.91E+09	882.06
Storage*Arc	793.30	13.12	60.43	<.0001	7.89E+09	3651.71
Arc*Arc	352.01	15.15	23.22	<.0001	1.17E+09	539.25
Arc*Refinery	76.95	23.48	3.28	0.0011	23212475	10.73
Storage*Arc*Arc	-58.51	7.57	-7.72	<.0001	1.29E+08	59.60
Storage*Arc*Refinery	-30.00	11.74	-2.56	0.0108	14119147	6.53

Comparison of the results highlights similar trends in the significance of factors and various interactions. Within both models, pipeline and storage capacities show significant impact on the availability of military grade fuel at critical nodes. Similar two-factor interactions and second order interactions are also significant. The re-strike model includes several three term interactions that show relevance beyond what is present in the single strike model. In both models, refinery factors were not independently significant. However, the factor associated with refineries can remain in the models because both experiments revealed significant interactions with refinery interdiction levels as a component.

As a result of both experiments, hypothesis $H_{3.1}$ is rejected, which supports acceptance of the alternative hypothesis $H_{3.1A}$; a combined strategy of supply and network interdiction significantly impacts the availability of military grade fuels at critical locations. Although refinery interdictions are not significant factors, their significant interaction with other factors supports their inclusion in the model. This hypothesis is therefore confirmed for both strike scenarios and across all factors.

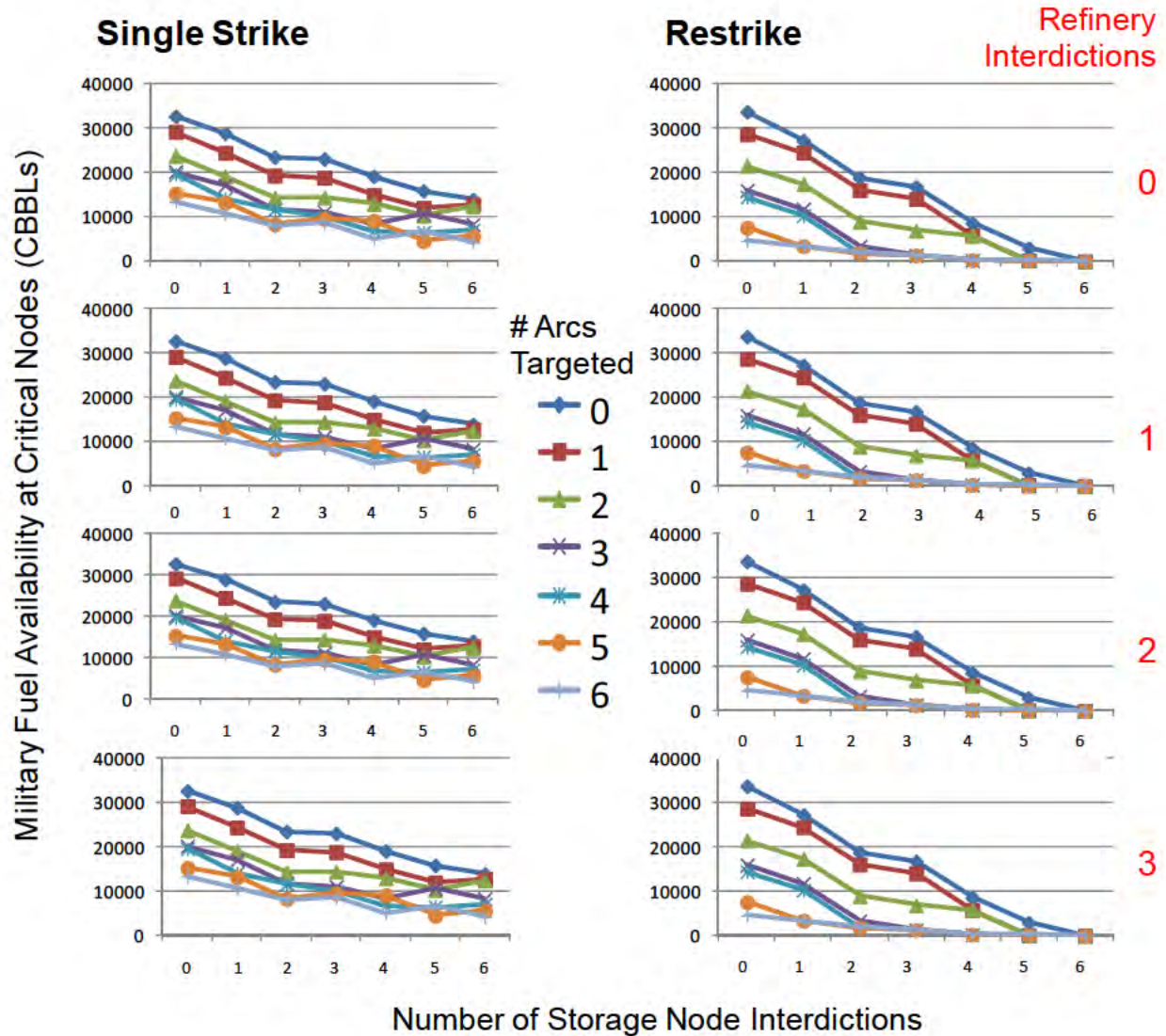


Figure 20: Experimental Data Comparison

Comparison of the impact of various factors on the practical availability of military grade fuel at critical locations is evident in Figure 20. There is substantial improvement for the interdictor in the re-strike scenario, because the increased time interval of disruptions greatly reduces fuel availability to the adversary's critical locations. The charts associated with re-strike on the right side of Figure 20 show drastic reductions, particularly at higher interdiction levels where availability falls to zero. In all courses of action within the single strike scenario, the

adversary will maintain some ability to access petroleum products in this scenario. This is not true of re-strike options, where fuel stocks at critical nodes are quickly rendered non-existent.

Another important observation in Figure 20 reveals that increasing the number of refinery interdictions does not appear to have any practical impact in the availability of refined petroleum within the time horizon. This is not unexpected since refinery factors were not independently significant when tested along with network infrastructure. It is now clear that the impact of refinery disruption on fuel availability that showed some promise in experiment 1 is insignificant when tested with network interdictions under the scenario parameters and timeframe. This result does not invalidate experiment 1, but it does demonstrate that the impact of refinery interdiction on fuel availability is insignificant when analyzed alongside higher pay off target factors in the given scenario and timeframe.

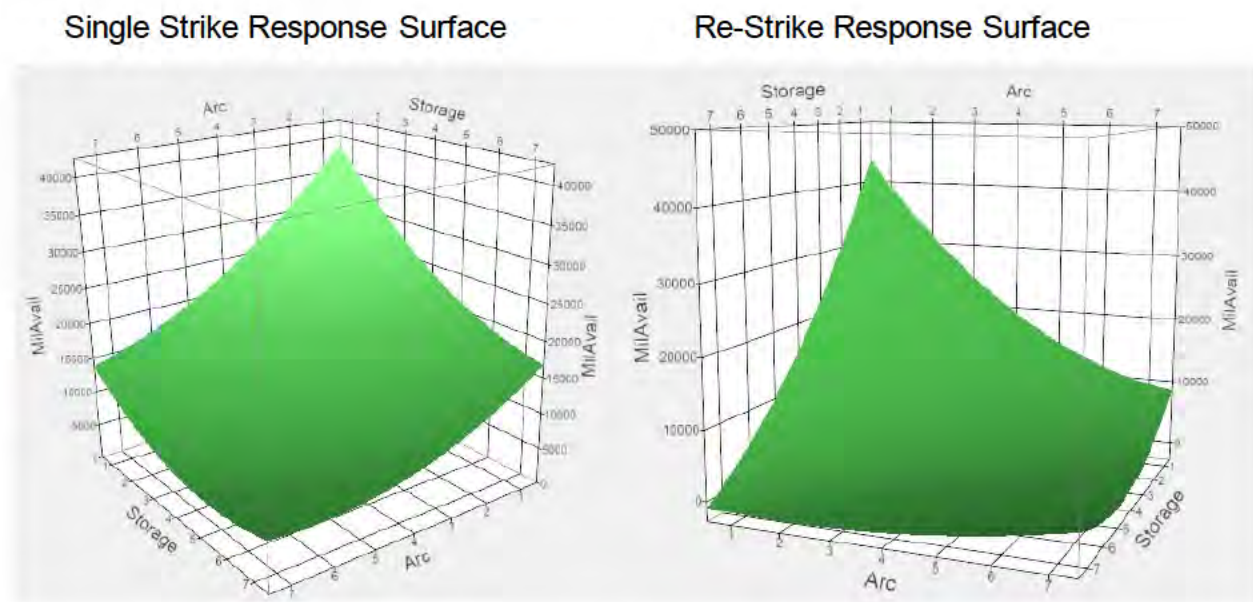


Figure 21: Scenario Empirical Surfaces for Significant Factors

Removing refinery operations from the empirical model would not significantly impact its predictive power as demonstrated by multiple iterations processed in JMP11. Figure 21

shows the streamlined models for storage and arc interdictions developed in JMP11 for single strike and re-strike courses of action. These figures represent the empirical model defined by the parameters in Table 17. The use of high order models produces a surface that allows the analyst to identify the region best suited to meet the needs of the combatant commander. Within this scenario, the re-strike response surface clearly demonstrates a greater area of acceptable fuel availability with options that require fewer independent targets. However, re-strike will require additional interdiction resources required to ensure that the network infrastructure remains offline for a deterministically modeled time period.

Determining how these competing scenarios will impact the surrounding economy requires analysis of the magnitude of economic loss induced by the interdiction strategy. The results of the experiment reveal that there is a greater magnitude of variation within the data set for the value of economic losses. Initially, the single strike scenario suggested substantial violations of the constant variance assumption required to implement design of experiments. As observed in Figure 22, the predictive model in the left figure and the associated residual model in the right figure indicate a severe conical shape that indicates the presence of non-constant variance within the model run.

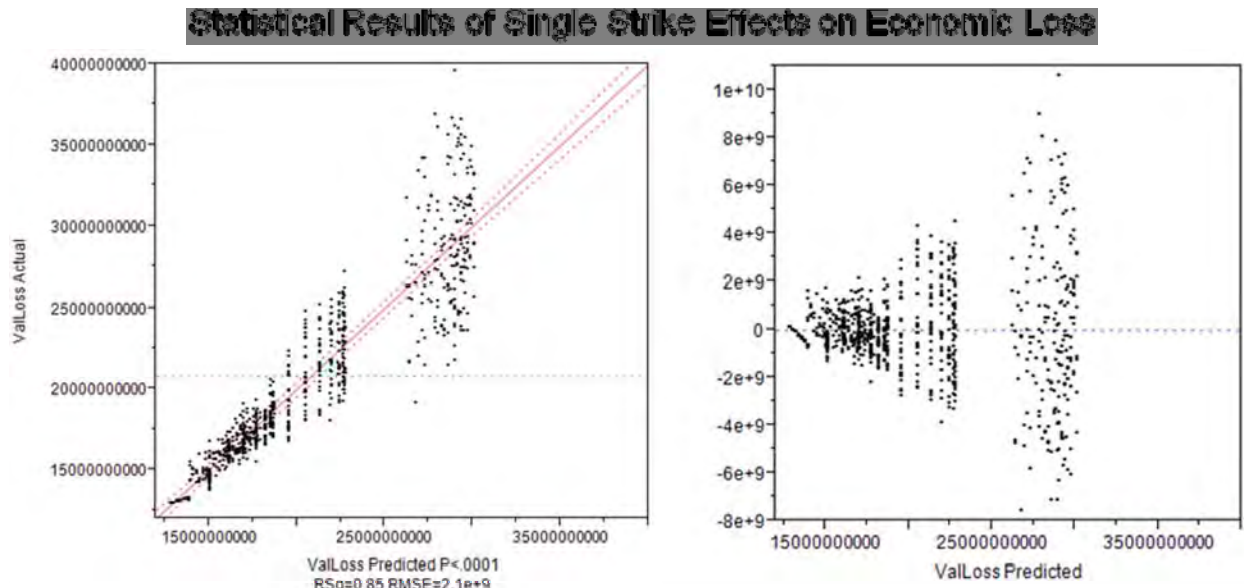


Figure 22: Statistical Residual Analysis of Single Strike Impact on Value of Economic Loss

The presence of non-constant variance violates an underlying principle required for the use of design of experiments. Therefore, the use of a transformation is appropriate. Due to the size of the numbers in question, transforming the value of the economic loss by using its logarithmic value is a possible approach to alleviate issues with increasing variance. The natural logarithm of each experiment replication transforms the value of economic loss for this result. The recalculated results appear in Figure 23, which apply the transformation to each response data point. The residual analysis in the right side of Figure 23 shows a much improved residual analysis. While there is still some remaining conical shape, several outlying data points exaggerate its severity. The improvement indicated by the residual analysis for the logarithmic transformation in Figure 23 indicates a more plausible compliance with constancy of variance assumptions. The presence of non-constant variance likely resulted from the increasing variation associated with each interdiction factor setting. As the model adds interdiction targets to the scenario, they are accompanied by a distribution that increases the variability within the model.

Fewer interdiction points results in less variation potential within the model. Another method of reducing the presence of non-constant variance would be an experimental design that limits the factor settings to a similar amount of interdictions. Although the experiment would explore a smaller decision space, there would be less variation between the factor settings.

LOG Transformation of Single Strike Impact on Economic Loss

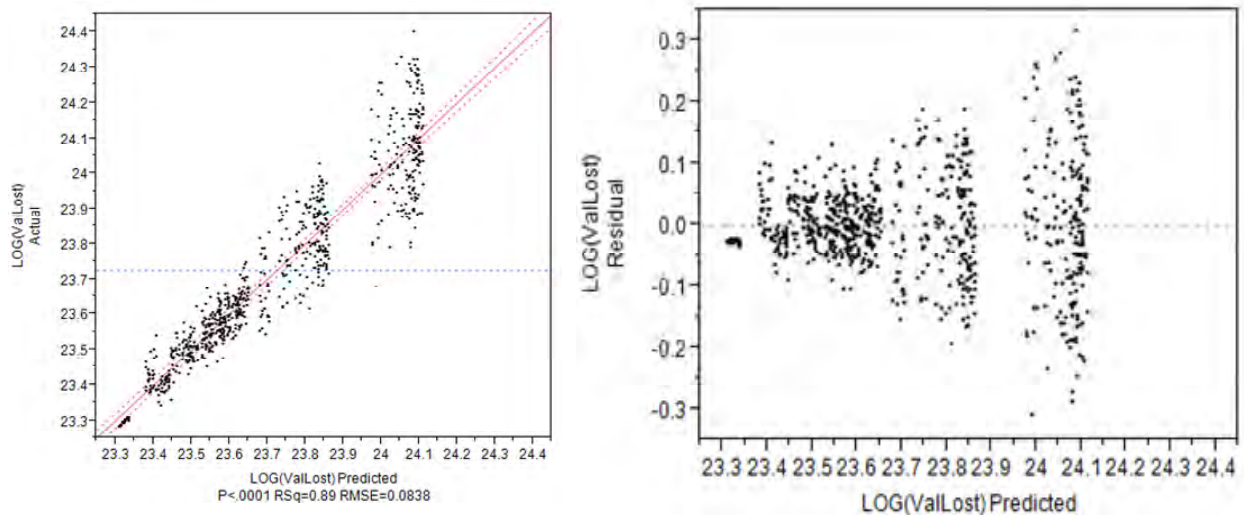


Figure 23: LOG Transform Residual Analysis of Single Strike Impact on Economic Loss

The re-strike scenario statistical analysis shows no indication of the problems with constant variance that were present in the single strike analysis. In fact, the loss of economic value shows extremely tight statistical results in comparison to the single strike option. The results of this experiment are shown in Figure 24 and include a residual chart on the right. The dispersion pattern of the residual analysis suggests that the assumption of non-constant variance is achieved. Additionally, the predictive power of this model indicates a more capable model with an R-squared adjusted value of .99. This result suggests that within this re-strike scenario, the model can predict value of economic losses with very low levels of variance. This is particularly useful when precise knowledge of the potential cascading effects is appropriate, such as a future nation building scenario.

Statistical Analysis of Re-Strike Impact on Value of Economic Loss

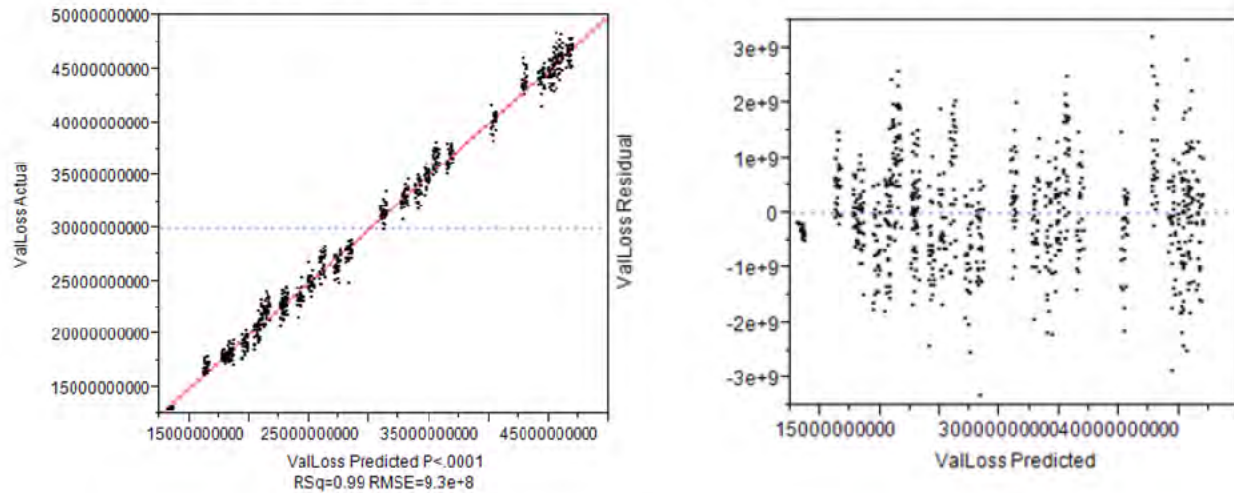


Figure 24: Residual Analysis of Re-Strike Impact on Value of Economic Loss

Because the empirical model of the single strike experiment uses a logarithmic transform, direct comparison of results is less apparent. However, both models clearly indicate statistical significance for all three single factors and several interactions and higher order terms as represented in Table 18. Both models indicate an acceptable level of predictive power as shown in the summary of fit portion of Table 18. Additionally, the inclusion of all three statistically significant single factors in the t -statistic results in Table 18 (highlighted in green) provides sufficient evidence to reject Hypothesis $H_{3,2}$. The results of the experiment support the conclusion of its alternative; refinery supply and network interdiction significantly impacts the measurable value of economic losses based on unmet demand. This hypothesis remains valid for all three interdiction factors in this scenario.

Table 18: Statistical Comparison of Experimental Results for Single Strike and Re-strike

Scenario						
Summary of Fit	Single Strike	Restrike				
RSquare	0.891	0.991805				
RSquare Adj	0.889	0.99171				
Root Mean Square Error	0.083	9.29E+08				
Mean of Response	23.725	3.01E+10				
Observations	784	784				
Analysis of Variance						
Source	DF	SS	MS	F Ratio	Prob > F	
Single Strike (Using Logarithmic Scaling)						
Model	7	44.13	6.30472	897.77		
Error	776	5.44	0.00702		Prob > F	
C. Total	783	49.58			<.0001	
Restrike						
Model	9	8.09E+22	8.99E+21	10408.73		
Error	774	6.68E+20	8.64E+17		Prob > F	
C. Total	783	8.16E+22			<.0001	
Parameter	Estimate	Std Error	t Ratio	Prob> t	SS	F Ratio
Single Strike (using Logarithmic Scaling)						
Intercept	22.944547	0.025965	883.68	<.0001		
Refinery	0.24	0.00953	25.4	<.0001	4.53	645.33
Arc	0.03	0.00149	20.29	<.0001	2.89	411.54
Storage	0.004	0.00149	2.86	0.0044	0.057	8.17
Refinery*Refinery	0.047	0.0029	15.9	<.0001	1.77	252.75
Refinery*Arc	-0.009	0.0013	-6.79	<.0001	0.32	46.14
Arc*Arc	-0.005	0.0008	-6.35	<.0001	0.28	40.36
Refinery*Refinery*Refinery	-0.021	0.0044	-4.76	<.0001	0.15	22.63
Restrike						
Intercept	-5.03E+08	3.43E+08	-1.47	0.1431		
Refinery	1.00E+10	1.06E+08	94.86	<.0001	7.77E+21	8998.56
Arc	966080122	49548758	19.5	<.0001	3.28E+20	380.15
Storage	75492911	16595406	4.55	<.0001	1.79E+19	20.69
Refinery*Refinery	1.63E+09	33190812	49.02	<.0001	2.08E+21	2402.52
Refinery*Arc	-1.74E+08	14843383	-11.72	<.0001	1.19E+20	137.25
Arc*Arc	-1.76E+08	9581362	-18.41	<.0001	2.93E+20	338.87
Refinery*Refinery*Refinery	-6.80E+08	49477942	-13.74	<.0001	1.63E+20	188.85
Refinery*Refinery*Arc	-87059715	16595406	-5.25	<.0001	2.38E+19	27.52
Arc*Arc*Arc	60036653	5975029	10.05	<.0001	8.72E+19	100.96

Using a comparison of the empirical models developed using the parameters for each scenario that were shown in Table 18, the modeler can assess suitable response surfaces to determine the range of the decision space appropriate to support the concept of operations. Assessing the results from Table 18, the involvement of storage interdiction at target nodes has considerably less practical impact on economic losses in terms of observed reductions. Despite its statistical significance, the critical storage node interdictions do not provide nearly the impact on the value of economic losses that are found in refinery and pipeline disruptions in this scenario during the specified time horizons. The strategist should anticipate that the network will continue to deliver fuel to the other 70 demand locations over the time horizon despite the loss of specific storage capacity locations. Therefore, the most meaningful surface profile involves refinery and pipeline factors and is presented in Figure 25. This result compares the resulting model from the single strike scenario on the left of Figure 25 and the re-strike scenario on the right. Despite the transformation used in the single strike results and the much lower variance in the re-strike option, the surfaces show striking similarities in shape. This indicates that the impacts resulting from refinery and pipeline interdictions consistently affected the value of economic losses. This result is effective in validating the responsiveness of the network model to parameter adjustments.

Surface Profile Comparison of Single Strike and Re-Strike Empirical Models

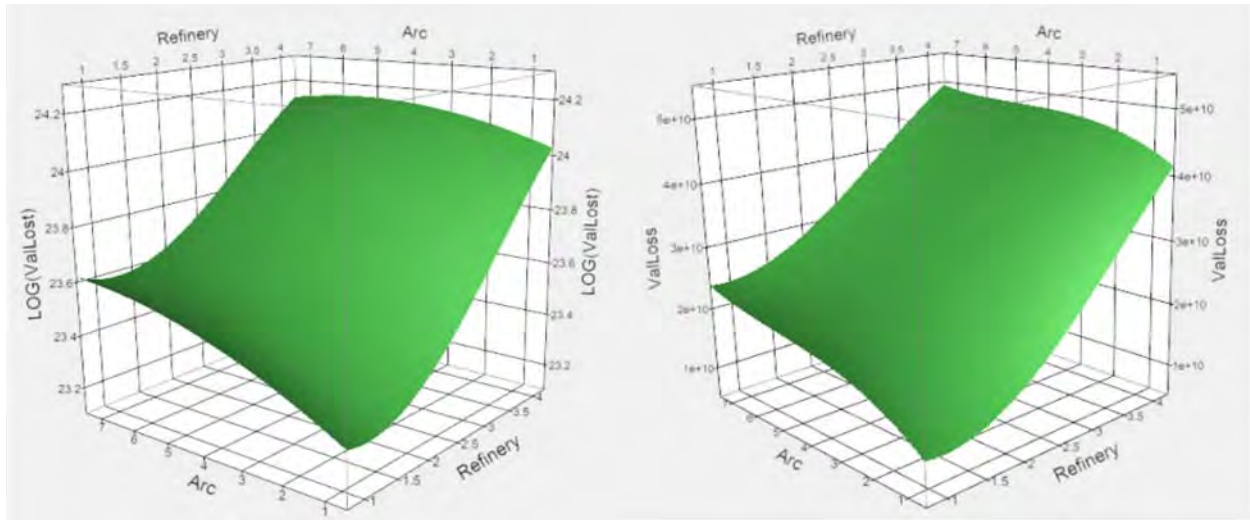


Figure 25: Surface Profile Comparison of Single Strike and Re-strike Empirical Models for Impact on Lost Economic Value

The practical analysis of impacts on the value of the economic losses shows a large increase for the re-strike scenario. This is expected because the infrastructure remains off line for a longer time period, which will force the model to accrue larger unmet demand resulting in higher economic loss. This impact is evident in the comparison of the practical results shown in Figure 26. There is a clear increase based on the refinery factor levels that is evident in the chart. This impact of this difference is essential to determining cascading effects.

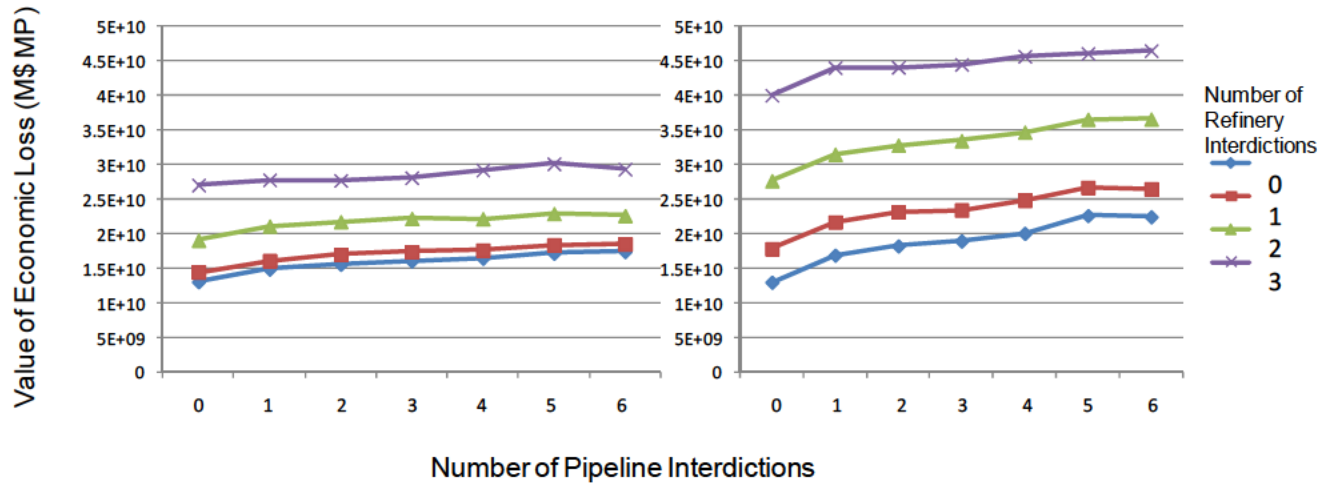
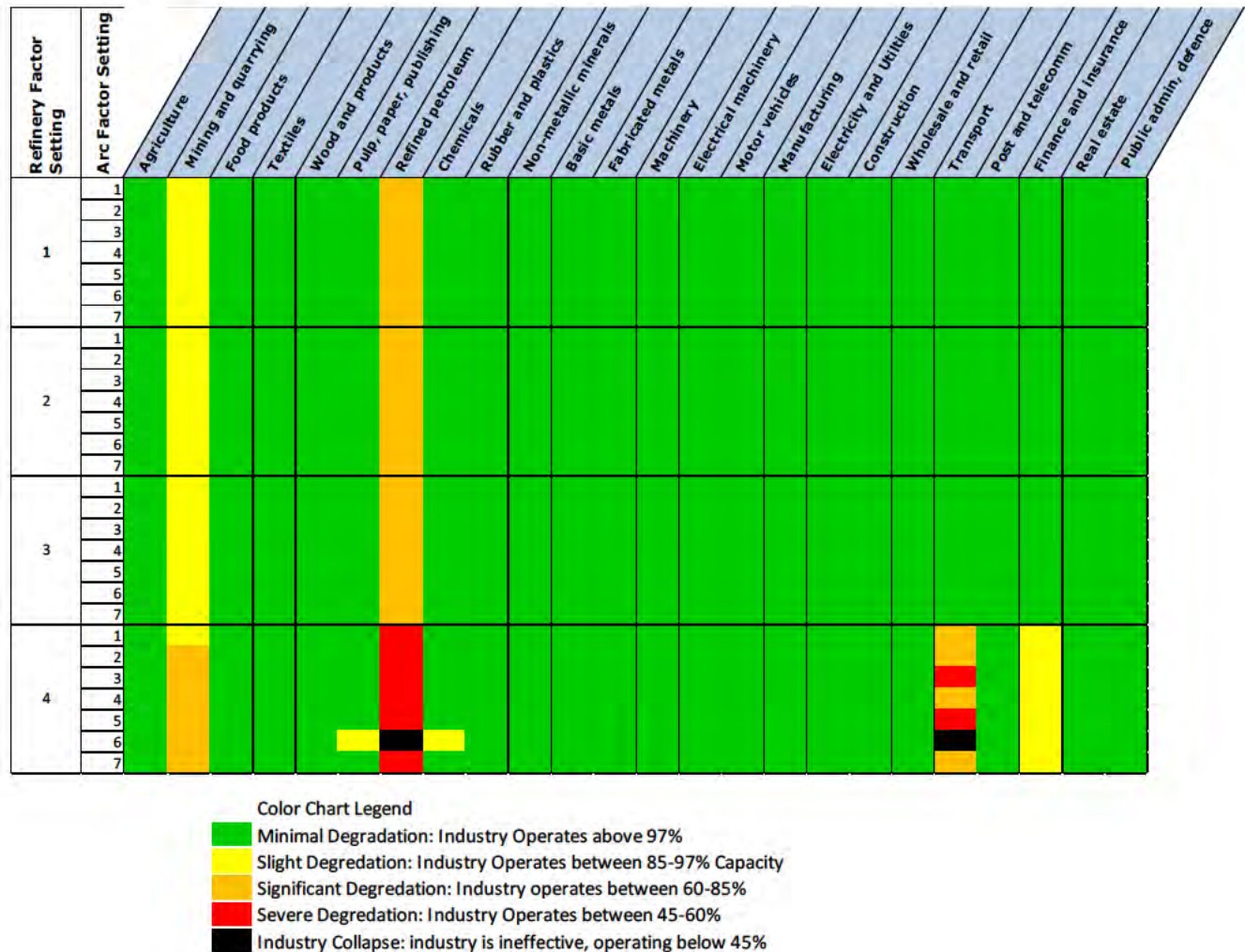


Figure 26: Practical Comparison of Single Strike and Re-strike Scenario Impact on Value of Economic Loss

Analysis of the effects on industry for the single strike scenario reveals limited cascading impacts in the mining and transportation sectors. The finance sector begins to feel the effects of limited availability, probably due to the significance of oil and gas production as a bedrock industry for this national economy. The cascading effects do not begin to reverberate through other industries under this scenario and time horizon. However, as refinery interdictions increase, the potential results from the degradation of the transportation industry are a risk to the entire economy during the 90 day period. The impacts under each type of interdiction level are shown in Table 19 and indicate an economy that remains stable within most critical sectors. The chemical and paper industries show some slight degradation at the most severe levels of interdiction. The interdiction of a subset of critical nodes proved capable of limiting the severity of secondary economic effects while denying fuel reserves to the adversary at decisive locations.

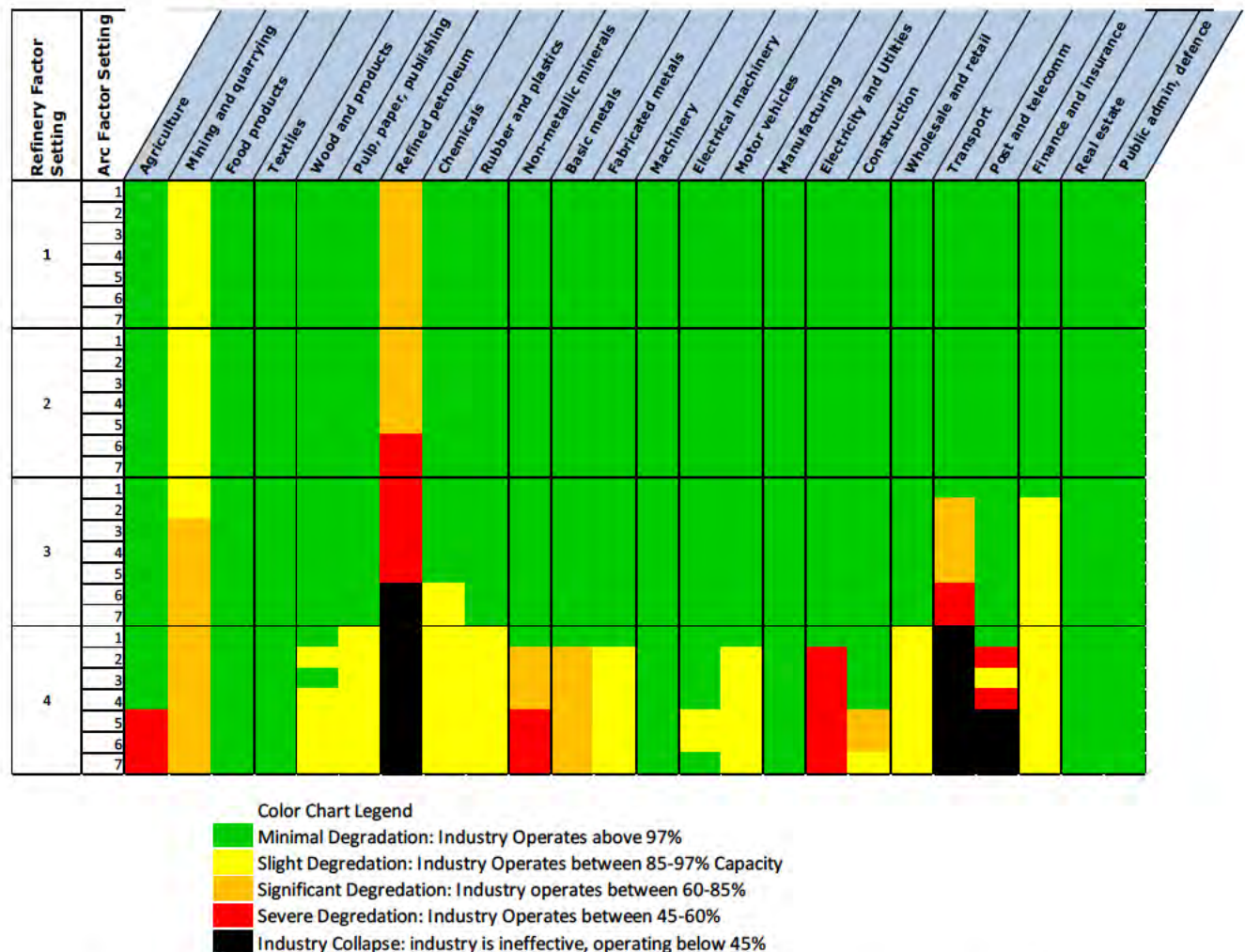
Table 19: Cascading Effects of Single Strike Interdiction Scenario on Selected Industries



The re-strike scenario showed greater potential for cascading impacts as evident in Table 20. As the factor settings increase, there is potential for industry collapse in the transport and finance industries. Equally concerning is the swiftness of degradation in the agricultural industry, which shows minimal degradation until reaching a crossover point at higher refinery factor settings. Beyond this crossover point, the impact becomes severe. Similar trends appear in several other industries including electricity and utilities. Because agriculture and utilities are essential to support self-sufficiency and quality of life in most economies, the cascading impacts of losses to these sectors may compound quickly. These are essential industries to everyday life

that appear to be approaching a crossover point that indicates a proximity to industry collapse in this scenario. Such a collapse will likely reverberate further throughout the economy. The impacts of this phenomenon may warrant further investigation.

Table 20: Cascading Impacts of Re-Strike Scenario on Selected Industries



The re-strike scenario has revealed several key insights that are essential to properly support decision making. The re-strike scenario showed a capability to completely strangle the availability of military grade fuel at key locations. Other scenarios failed to demonstrate this level of effectiveness in reducing the ability of an adversary to supply its critical locations. Additionally, statistical analysis of re-strike showed much lower and more consistent variance.

This resulted in a model with greater predictive power and more consistency in the resulting data points. This consistency leads to a tighter estimate of the value of economic losses. The magnitude of economic losses is greater, which results in higher levels of degradation across a range of other industries. However, analysis does not include the effects of economic recovery during or after a 90-day campaign.

4.7 Experiment 4: Natural Disaster Scenario

Another potential application of the proposed model is prediction of the impact and cascading effects resulting from the disruption caused by a natural disaster such as a hurricane or earthquake. A notional example using the network case study data is presented in Figure 27 with a potential projected path of a weather related disruption. This notional example includes a disruption to storage and pipeline infrastructure points that are directly in the path of the disruption. This also includes the precautionary or residual impacts on major infrastructure including the importation and refinement points that are highlighted in yellow. This scenario results in a disruption factor for the highlighted refinement and importation points, and two disruption factors for storage and pipeline facilities. In lieu of military availability, the model measures the availability of resources at proximate population centers. The weighted value associated with $Q_{j,p}$ receives an appropriate assignment in order to ensure network consistency, and the warm-up period is reduced to four days to allow some buildup of resources by the network manager.

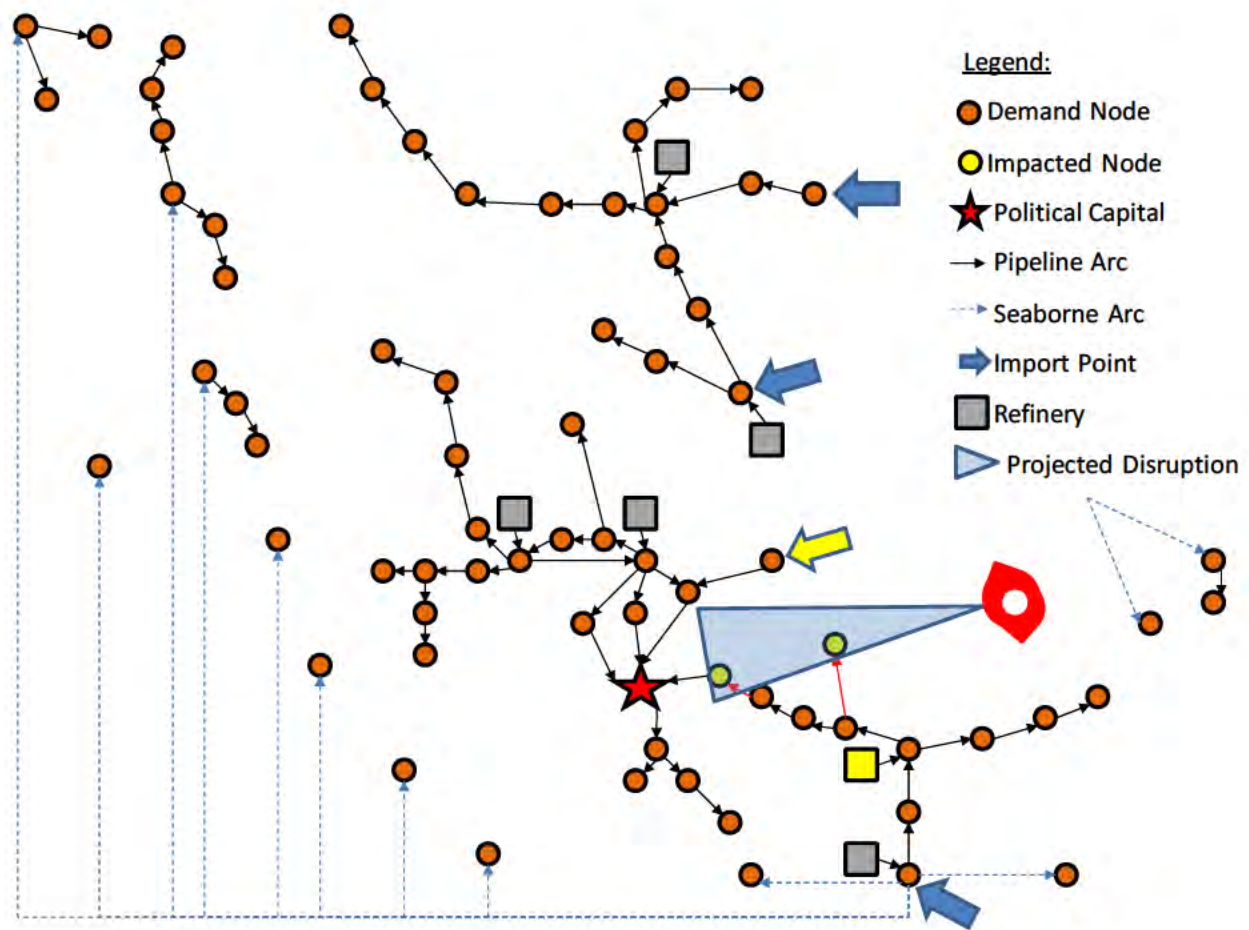


Figure 27: Natural Disaster Network Scenario

There are four factors within this experiment. They include one refinery, one import point, two storage facilities, and two pipelines. The refinery and import point factors require a binary setting to indicate whether a disruption occurs in the experimental run. The arc and storage node factors require three settings to indicate whether the disruption impacts zero, one, or two locations. This experiment requires 144 model runs to complete four replications. The model collects response data for supply availability at the political capital and impacted nodes as highlighted in Figure 27 for the first three weeks following an interdiction. The value of economic losses is assessed using the same criteria for previous experiments.

The results for this experiment were statistically significant. The statistical analysis presented in Figure 28 show extremely tight variances for the empirical model shown in Table 21. This low variance is partly a result of the practical reduction in the critical availability, which is only reduced by less than 4% as a result of the natural disaster. However, there are significant terms present in the statistical model, including the arc, storage, and several interaction terms highlighted in Table 21.

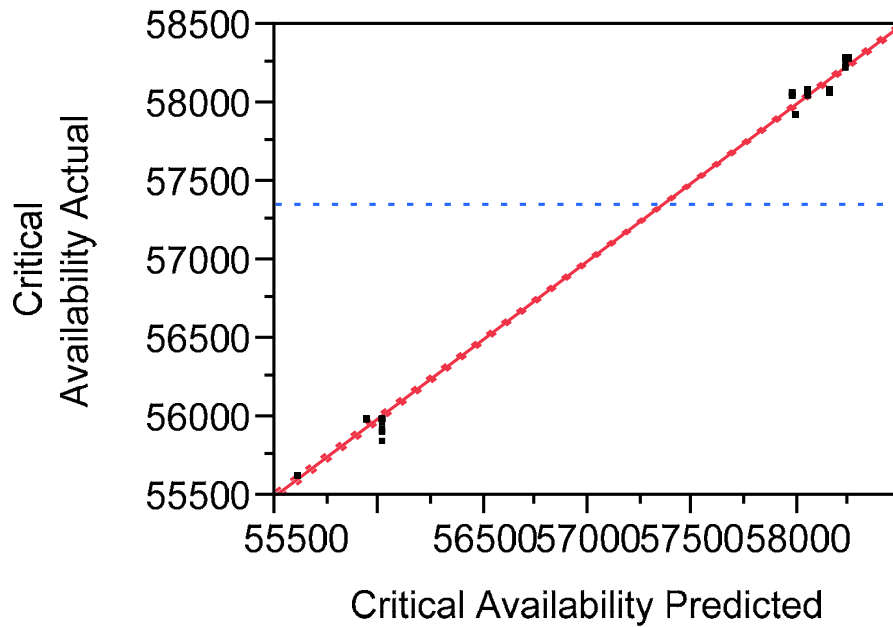


Figure 28: Predictive Analysis of Natural Disaster Scenario on Critical Availability

The t -statistic presented in Table 21 provides sufficient statistical evidence to reject hypothesis $H_{4.1}$ and confirm its alternative $H_{4.1A}$; Natural Disaster disruptions significantly impact the availability of fuels at the critical supply locations. This conclusion holds true for arc and storage factors as well as their interactions and second-order effects. Hypothesis $H_{4.1}$ is confirmed for supply factors, which do not show statistical significance in limiting availability to critical local economies. Additionally, the model shows excellent predictive power with an R -squared value near 1. These likely results from the limited impact of a single refinery and

importation point. The network manager has significant resources to apply to circumvent these supply disruptions within the model. This estimate is realistic due to the greatly increased ability to recover from a natural disaster of limited scope as opposed to a widespread and potentially catastrophic interdiction campaign. The network manager can devote the restoration resources to these specific locations with less collateral risk to recovery operations or employees.

Table 21: Statistical Analysis of Natural Disaster Impacts on Availability

Summary of Fit

RSquare	0.997307
RSquare Adj	0.997209
Root Mean Square Error	56.90915
Mean of Response	57357.37
Observations (or Sum Wgts)	144

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	5	165485603	33097121	10219.42
Error	138	446934	3238.6509	Prob > F
C. Total	143	165932537		<.0001*

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob> t
Intercept	55798.19	19.55	2853.60	<.0001*
Arc	1104.90	5.80	190.23	<.0001*
Storage	118.72	5.80	20.44	<.0001*
(Arc-2)*(Arc-2)	-1198.12	10.06	-119.10	<.0001*
(Arc-2)*(Storage-2)	-81.23	7.11	-11.42	<.0001*
(Storage-2)*(Storage-2)	-133.99	10.06	-13.32	<.0001*

Unfortunately, the results for this analysis do not show visible variation for response surfaces fitted to the model when using a graphic scaled at zero. However, a graph of the region of interest is presented in Figure 29. This graphic only shows the response region where the changes are observed and the vertical axis is not scaled to zero. While representative of the volatile region of the design, this surface would appear flat to the naked eye with all axes scaled

to zero. The results of this estimate could inform a strategy for the network manager to mitigate local impacts. For example, planned shutdowns of the refinery and import points may reduce the potential recovery time following a natural disaster. Additionally, the network manager could reallocate supplies from other facilities to temporarily backfill the expected losses. Finally, the restoration services should focus on the damage to the network infrastructure. It is particularly important to maintain the electrical power necessary to operate pumping stations and transshipment nodes. Additionally, the exposed portions of pipelines that might suffer physical impacts or portions that are susceptible to mudslides and other predictable natural disasters should receive sufficient stocks of repair parts and technicians to enable a rapid restoration process. This restoration strategy could sufficiently inform the network manager and allow better planning and forecasting of expected impacts. Changes in the restoration distribution parameters could allow the strategist to investigate the value of stockpiling repair materials and teams.

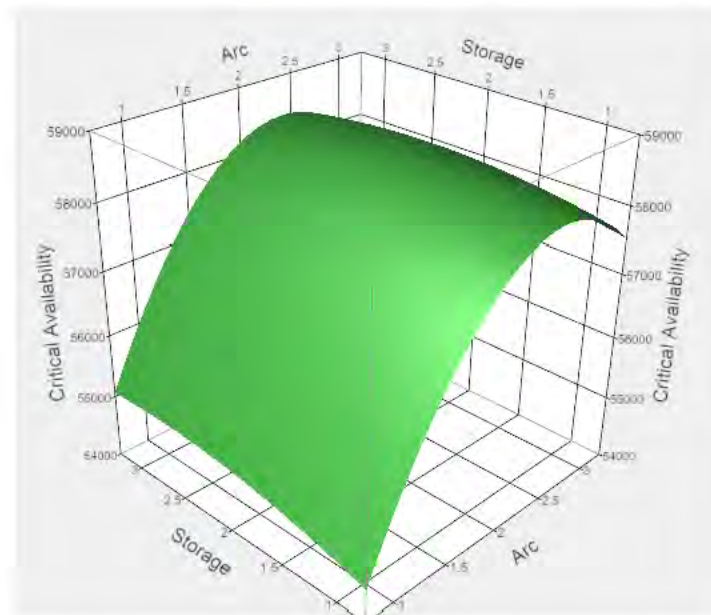


Figure 29: Scaled Surface Profile of Empirical Results of Natural Disaster Impacts on Critical Supply Availability

The results for the impact on the value of economic loss show statistical significance for the refinery outage and pipeline disruption as highlighted in Table 22. These results support the rejection of hypothesis $H_{4.2}$. The results confirm the alternate hypothesis for pipeline and refinery disruption factors; natural disaster disruptions will significantly impact the measureable value of economic losses based on unmet demand. Storage and Import factors were statistically insignificant in this experiment, indicating that limited scenario natural disaster disruptions of similar infrastructure types is not critical enough to increase the value of economic loss in a national economy. Further analysis of this problem set might apply a similar experiment to a local or regional economy where high resolution data exists.

Table 22: Statistical Analysis of Natural Disaster Impact on Value of Economic Loss

Summary of Fit

RSquare	0.685757
RSquare Adj	0.681299
Root Mean Square Error	1.031e+9
Mean of Response	1.35e+10
Observations (or Sum Wgts)	144

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	2	3.2704e+20	1.635e+20	153.8483
Error	141	1.4986e+20	1.063e+18	Prob > F
C. Total	143	4.769e+20		<.0001*

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob> t
Intercept	8.3152e+9	3.436e+8	24.20	<.0001*
Refinery	2.9575e+9	1.718e+8	17.21	<.0001*
Arc	355888489	1.052e+8	3.38	0.0009*

The total value of economic losses resulting from this scenario was insufficient to produce a noticeable cascading effect in any sectors other than refined petroleum and mining. This result is shown in Table 23. This result is not unexpected given the analysis of experiment 2. However, since the model only impacts a geographically isolated area of the decision space where storage is not affected outside the impact zone, a local input-output matrix is more appropriate for this analysis. Future research may require that regional or local economic data conform to the region most affected by a disruption. This adjustment would provide a more relevant measurement of the impacts on local industries. Additionally, an earthquake scenario utilizing an unpredicted catastrophic disruption of all storage and pipeline facilities in a geographical area would provide risk management metrics necessary to mitigate an unplanned natural disaster.

Table 23: Cascading Impacts of Natural Disaster Disruptions on Select Industries

Refinery Factor Setting		Arc Factor Setting																								
1-2	1	Agriculture	Mining and quarrying	Food products	Textiles	Wood and products	Pulp, paper, publishing	Refined petroleum	Chemicals	Rubber and plastics	Non-metallic minerals	Basic metals	Fabricated metals	Machinery	Electrical machinery	Motor vehicles	Manufacturing	Electricity and Utilities	Construction	Wholesale and retail	Transport	Post and telecom	Finance and insurance	Real estate	Public admin. defence	
	2																									
	3																									
	4																									

4.8 Sensitivity Analysis

By implementing the Leontief model using graduated levels of petroleum sector productivity from full functionality to complete collapse within the impacted national economy, the impacts on supported industries are indicated. Most of these industries have a critical point associated with depleted fuel availability beyond which their productivity collapses. These results are shown in Figure 30, which depicts traces of productivity for selected industries

against the depletion in fuel availability. These results are consistent with experimental analysis of the impact of cascading effects. The results from the designed experiment could utilize this chart to determine the level of impact on a specific industry for the economy in the case study. In this case, the Leontief model was not adjusted for the smaller scale of the problem.

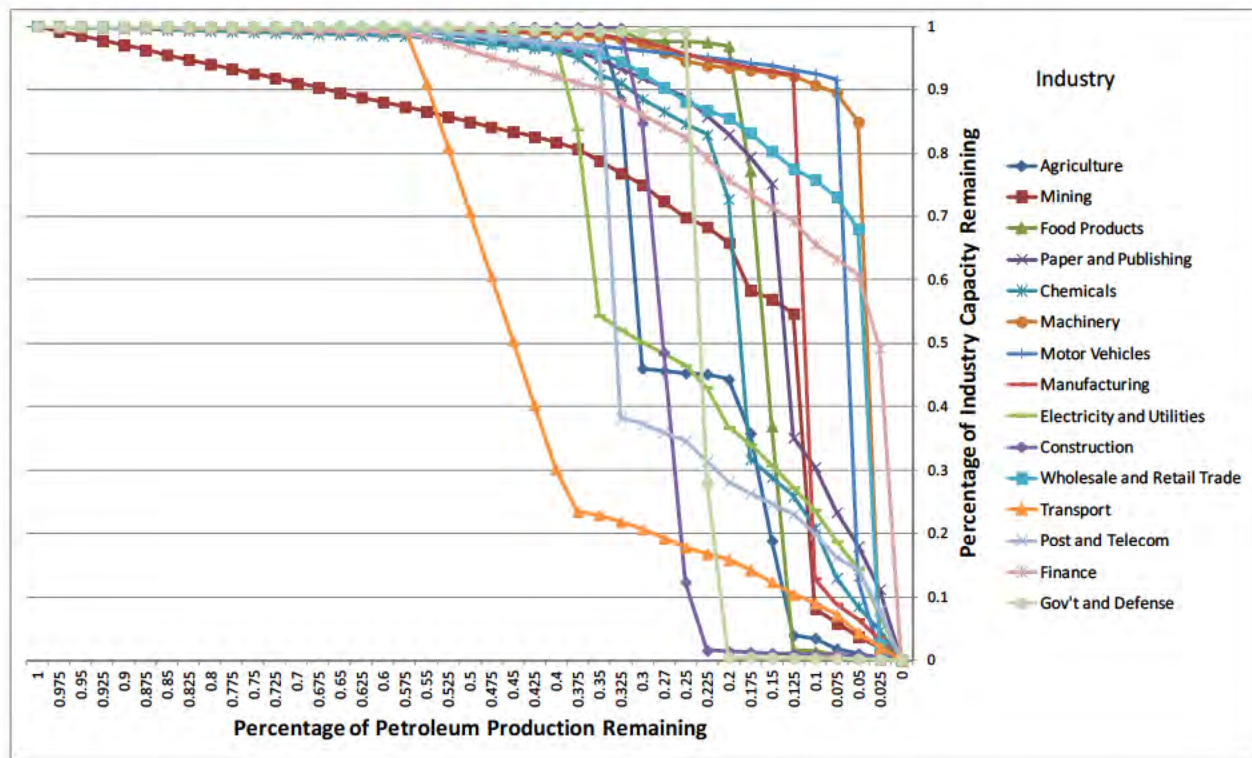


Figure 30: Sensitivity of Case Study Economy to Availability Losses in Refined Petroleum Products

The refined petroleum network manager may have some ability to maintain productivity in selected industries based on their strategic priorities. By altering the objective function shown in equation (18), the model will redistribute remaining capacity amongst selected industries as necessary. The analyst is then able to alter the objective function and conduct sensitivity analysis on the results. For example, a scenario may exist where the adversarial decision maker desires to maintain productivity in the transportation, government, and electricity/utility sectors

as long as possible. This objective function would not include other industries in the objective function, although petroleum remains bounded by the percentage of full capacity that is denominated in the horizontal axis in Figure 31.

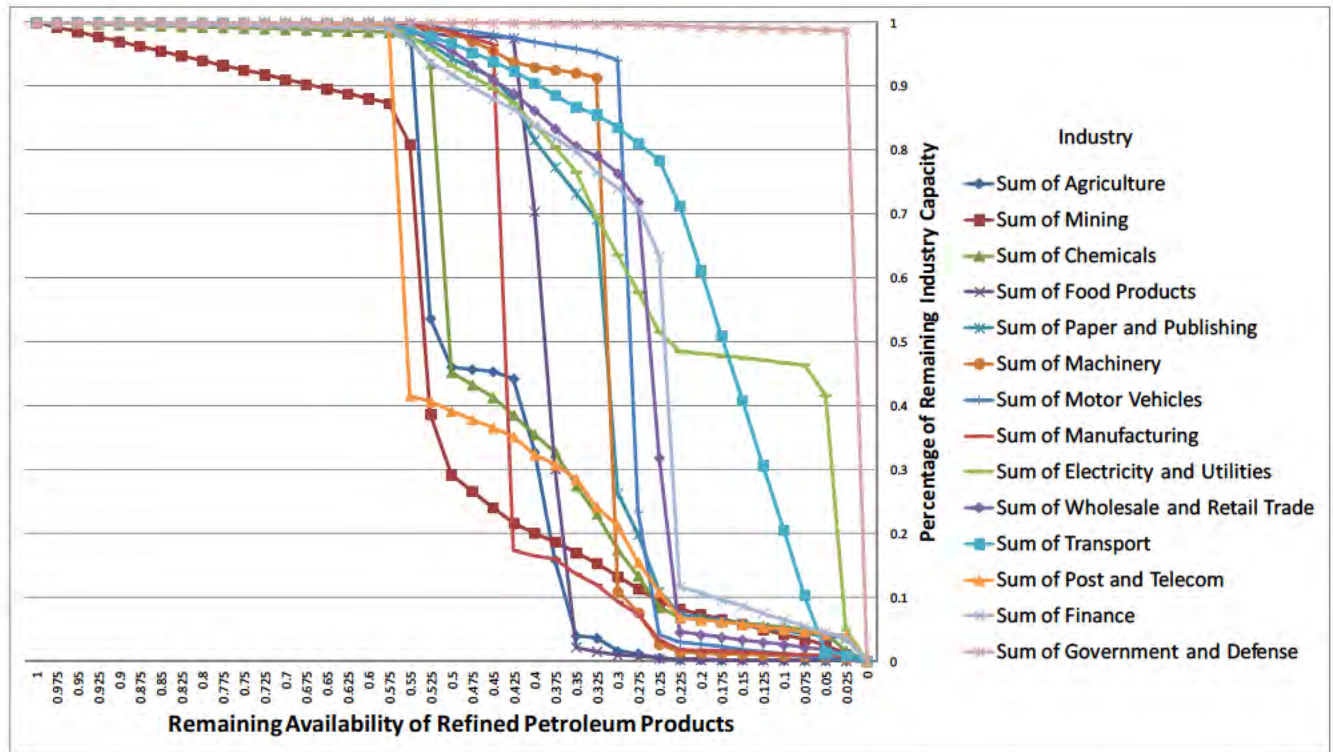


Figure 31: Sensitivity of Case Study Economy to Limited Petroleum Fuels with Select Priorities

Finally, the adversary may chose to limit the remaining petroleum to specific industries while maintaining other critical industries. For example, if the agriculture industry is a political enemy of the regime, a decision maker might restrict the sale of resources and products for agricultural purposes. The impacts of this type of restriction are evident in Figure 32. Several other industries in including food production and wood products decline significantly due to this restriction and the model allows similar analysis on all industries for which input-output data is available.

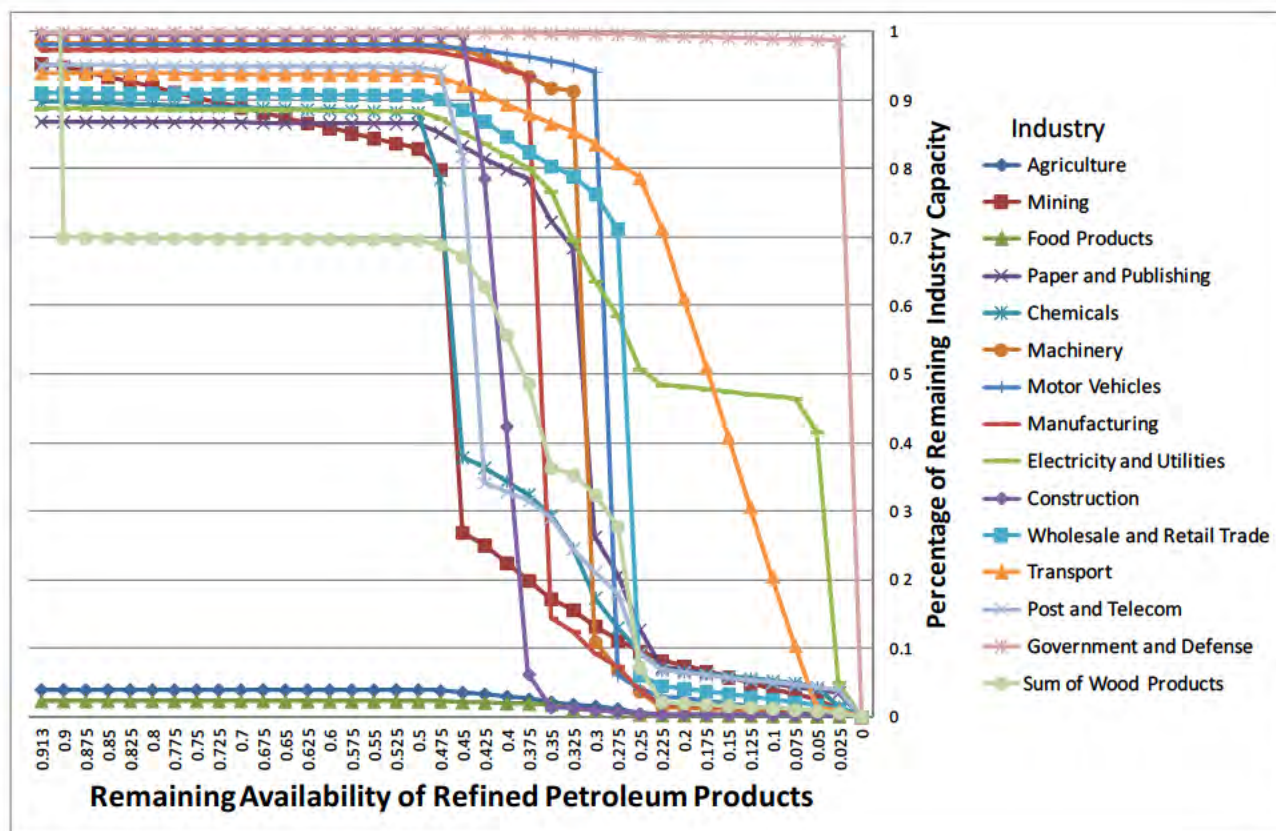


Figure 32: Sensitivity of Case Study Economy to Limited Petroleum Fuels with Select Priorities and Restrictions

4.9 Black Market Analysis Excursion

Countries suffering from limited production have long and troubled histories of black market theft and illicit activity targeted at transportation and shipment locations for petroleum products. Illicit petroleum traffickers often target polyduct systems and may gain necessary shipment information using complicit employees or by weaknesses or manipulation of the SCADA anomaly detection systems. Tapping into pipelines and illicitly reselling petroleum products is common practice within many distribution systems (“Black Gold on the Black Market,” 2012).

While the economic loss from oil theft over time is undisputed, the significance of the effects on the system remains less clear. The methodology from this study contains a mechanism to assess the losses caused by increasing levels of theft across a network of pipelines. Within the N_K sub-matrices, the network architecture is determined by a series of -1, 0, and 1 values as described in section 3.2. The use of the value 1 indicates that 100% of the refined fuel shipped from any transshipment node, D_j reaches the subsequent node, D_{j+1} in accordance with the assumptions of flow balance. However, the theft of resources directly from a pipeline is unknown to the network manager in magnitude and location resulting in unmeasured losses that occur along the shipment route. The modeler can represent the potential severity of this loss by applying a multiplier, g to the portion of the matrix that is affected. This multiplier would transform the 1 in an appropriate location of an N_K matrix to a reduced value such as .99 as an example of the estimate of lost volume. The reduced value describes a pipeline where 99% of the product shipped reaches its destination while illicit traffickers remove 1% of the flow.

Using such an approximation, the automated model will assess the impacts of increasing levels of illicit trafficking on the same pipeline segments from the interdiction experiment. Refinery and storage interdiction remain in effect for the excursion. The factor levels for black market theft range from 1-5% of the economy for this demonstration. When conducting the experiment using up to 3% theft rate out of each of the six pipeline segments, there was no significant impact on the availability of fuel to military locations or on the value of economic loss within the system. This result appears in Table 24, and the highlighted black market factors show no substantial contribution to the modeled responses of military availability or the value of economic losses. The contributions of Storage and Refinery interdictions and measured responses remain consistent with the results from Experiment 3.

Table 24: Analysis of Theft Rate up to 3%

Summary of Fit for Value of Economic Loss

RSquare	0.885247
RSquare Adj	0.883154
Root Mean Square Error	1.885e+9
Mean of Response	1.84e+10

Analysis of Variance

Source	DF	SS	Mean Square	F Ratio
Model	6	9.0206e+21	1.503e+21	423.0034
Error	329	1.1693e+21	3.554e+18	Prob > F
C. Total	335	1.019e+22		<.0001*

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob> t
Intercept	3.2108e+9	8.962e+8	3.58	0.0004*
Refinery	5.0417e+9	3.275e+8	15.40	<.0001*
Storage	164691063	51424436	3.20	0.0015*
BlkMkt	134230789	1.26e+8	1.07	0.2874
(Refinery-2.5)*(Refinery-2.5)	1.3517e+9	1.028e+8	13.14	<.0001*
(Refinery-2.5)*(Storage-4)	97000060	45995414	2.11	0.0357*

Summary of Fit for Military Availability

RSquare	0.886763
RSquare Adj	0.885048
Root Mean Square Error	2261.935
Mean of Response	22634.12
Observations (or Sum Wgts)	336

Analysis of Variance

Source	DF	SS	Mean Square	F Ratio
Model	5	1.3222e+10	2.6444e+9	516.8494
Error	330	1688394821	5116347.9	Prob > F
C. Total	335	1.491e+10		<.0001*

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob> t
Intercept	34844.358	536.4057	64.96	<.0001*
Storage	-3116.246	61.69932	-50.51	<.0001*
Refinery	-222.0628	110.3711	-2.01	0.0450*
BlkMkt	-95.64207	151.1319	-0.63	0.5273
(Storage-4)*(Storage-4)	179.939	35.62212	5.05	<.0001*
(Refinery-2.5)*(Refinery-2.5)	225.14727	123.3986	1.82	0.0690

However, when the level of interdiction is increased to 5% of the flow rate through all six critical pipelines, the black market factor impacts the value of economic loss at a statistically significant level. This result is demonstrated in Table 25 and shows that black market theft up to a 5% level will significantly impact the value of economic loss during the interdiction campaign. The removal of 5% of flow rates across these six polyduct accounts for over 300,000 barrels during a 90 day model run. While this loss is practically minor compared to the interdiction impacts caused by refinery and storage node disruptions, its presence will not influence the availability of military grade fuels at critical locations.

Table 25: Analysis of Theft Rate up to 5% on the Value of Economic Loss

Summary of Fit

RSquare	0.877908
RSquare Adj	0.876246

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	6	1.2336e+22	2.056e+21	528.5031
Error	441	1.7156e+21	3.89e+18	Prob > F
C. Total	447	1.4052e+22		<.0001*

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob> t
Intercept	2.8716e+9	8.066e+8	3.56	0.0004*
Refinery	5.1249e+9	2.967e+8	17.27	<.0001*
Storage	169363887	46593426	3.63	0.0003*
BlkMkt	176588613	83348854	2.12	0.0347*
(Refinery-2.5)*(Refinery-2.5)	1.3854e+9	93186852	14.87	<.0001*
(Refinery-2.5)*(Storage-4)	108694587	41674427	2.61	0.0094*
(Refinery-2.5)*(Refinery-2.5)*(Refinery-2.5)	-3.026e+8	1.389e+8	-2.18	0.0299*

The production of this model did call into question the practicality of such wide spread theft. The removal and illicit trafficking of over 300,000 barrels of fuels constitutes an industrial

sized undertaking when considering the level of effort required for shipping and profitably marketing such a huge quantity of liquid. However, further arithmetic analysis presented in Table 26 shows that this amount of fuel represents approximately 5 daily tanker truck loads stolen from each of six locations across a vast geographical area of potential infiltration. When considered in this context, it is not infeasible that a major criminal cartel could potentially move this much stolen product and remain undetected. A cartel could further diversify this process by increasing the number of theft locations across a polyduct arc.

Table 26: Feasibility Analysis of 5% Theft Rate

Arithmetic Analysis of Feasibility for 5% Black Market Theft Rate	
3163.95	Average Volume of 5% Black Market Loss (Hundreds of Barrels)
316395.10	Average Volume Loss in Barrels
5000.00	Capacity of a Standard Tanker Truck (US Gallons)
42.00	Gallons/Barrel (US)
119.05	Barrels/Truck
2657.72	Total Truckloads Required
90.00	Total Days of Model Run
29.53	Total Truckloads per Day
6.00	Minimum Number of Theft Locations
4.92	Maximum Number of Trucks per Theft Location

While the theft of fuel intended for use in the black market is insufficient to impact the model of cascading effects, the impacts of this fuel re-entering the local marketplace may bear consideration in a future study. The manipulation of the automated model to increase the level of theft would still require a feasibility analysis to ensure that the rates of illicit trafficking are within the known capacity of the suspected criminal enterprise.

4.10 Conclusions

The results demonstrate the capacity of an analyst or strategist to investigate factors within a known distribution network using a methodology that provides insight regarding the primary and secondary impacts of a fuel network interdiction strategy. The responses measured in fuel availability and valued using unmet demand provide the statistical means to determine which factors are most effective at producing desired effects. The propriety and capability of different courses of action can inform a recommendation for meeting a combatant commander's intent.

The network model proved versatile and effective for inclusion in various experiments. The use of experimentation is an effective means of exploring the decision space and selecting an appropriate course of action that supports decisive operations. The analyst can implement this methodology in order to achieve outcomes that improve the success of supported commanders while limiting the difficulty of follow on missions by managing cascading effects.

While the analysis was confined to critical military areas based on a concept of operations, the model provides the opportunity to analyze a variety of scenarios. Initial plans are subject to testing and alteration to meet specific strategic goals or mitigate impacts to a desirable level. All parameter and factor settings are flexible, allowing a wide variety of analysis.

V. Conclusions and Recommendations

5.1 Contributions of Study

The US Armed Forces enjoys the operational advantages provided by an ability to limit an adversary's access to strategic commodities. Petroleum and its refined products are key targets for this type of interdiction due to the prominence of energy resources in many aspects of military and economic portfolios. A number of tools exist that allow combatant commanders to conduct these interdictions against various portions of an adversary's infrastructure. While this study did not focus on the specific means of interdiction, various kinetic, diplomatic, economic, and cyber based tools may apply to disruption of a petroleum supply network.

The interdiction of a strategic commodity is a potentially powerful tool. The combatant commander has an obligation to limit the scope of disruption to the level necessary to reach the desired operational effect. The network model created in this study demonstrates a methodology to determine the impact of an interdiction strategy on military availability and adverse effects using experimentation. The study also demonstrated a tool that is available to investigate the degree of cascading effects using Leontief input-output modeling.

The results of a related case study showed how some factors may have no statistically significant impact on the strategic outcome as related to the availability of military grade fuels in the specified scenario. The strategist might consider the resources and cascading effects related to an interdiction campaign and determine whether the measureable impacts on the targeted areas justify the expense. A concept of operations that included future investment in the disrupted economy has an even higher interest in maintaining economic functionality.

5.2 Significance of Results

A series of notional scenarios demonstrated the features of the model. The results of the case study indicated no potential for the limitation of military fuel supplies using interdiction of refined petroleum imports in the time horizon of the scenario. While specific to this case study, the results clearly indicated that the network contained sufficient resiliency to ensure delivery of products to critical locations despite a disruption of imports. Given a longer time horizon, the effects of a blockade of imports could warrant further investigation. This result informs future planners that might consider the long term impact prior to initiating diplomatically and economically expensive boycott or embargo options. Additionally, interdiction of imports will cascade through other industries if the resulting disruption sufficiently lengthy.

Storage facilities represented the most promising target for limiting the availability of fuel to military targets while limiting cascading effects based on the scenario results. This appears to be a foregone conclusion since the lack of a facility to store and transfer fuel is necessary to maintain a military supply infrastructure. However, historical data from the Gulf War demonstrated that refinery points are priorities for interdiction with limited military success (Hall, 1998: 594). Experimental results in the case study showed that limitations on storage and delivery infrastructure was the most effective means of limiting military availability without inflicting cascading effects in the investigated scenarios.

Campaign strategies will affect disruption and cascading impacts with much less variance when the planner possesses the ability to re-strike or disrupt a facility for a consistent time period. Variance increases quickly as the interdiction campaign expands due to the unpredictability of restoration times.

When employed using a natural disaster formulation, the case study proved insufficiently disaggregated to reasonably predict the network impacts or cascading effects. Ideally, the impact of a local outage caused by a natural disaster should resource local economic and network data. The analysis did indicate how to investigate natural disaster scenarios.

5.3 Recommended Paths forward

The model exhibits the extent of constraints, capacities, and network infrastructure resolution available through open source research and publicly accessible data bases. This data informed the case study and allowed the construction of a functioning automated network model. Using more site specific information related to transshipment nodes, pipeline interactions, and refinery operations, a future endeavor could populate the constraint set with more precise information. The model could also extend into the supply chain of raw crude stocks that fuel refinery operations as an additional disruption point or capacity constraint.

Experimentation on this network model used a consistent time horizon implementation that calculated a daily optimization and updated the starting criteria prior to the subsequent iteration. Neither the network model nor resulting Leontief formulation involved a truly dynamic formulation. A potential improvement on this model would implement the network automation using precise time data involving the production and routing of petroleum products resourcing time dependent demand patterns. The potential model requires substantial engineering level data regarding pipeline and refinery function as well as established demand patterns. Such fidelity, however, will result in a larger model with greater solution complexity.

A model that is unconstrained by national boundaries may better accommodate more complex petroleum economy such as the OPEC members in the Persian Gulf region. In this

case, a complete regional supply and distribution network would allow the modeler to best represent the impacts of a disruption across multiple interdependent nations.

Additionally, an excursion investigating black market effects targeted at specified network arcs modeled the anticipated level of theft. The results provided insights on the impact of illicit trade in the refined petroleum industry. However, since this product will ultimately re-enter the local marketplace through black market sales, the impact on smaller regional economies remains unclear. Investigation into the impacts of black market sales on local economic conditions would provide further refinement on the impact of cascading effects.

While this study did not focus on the efficiency of the recommended automation package, there is potential for further investigation based on the needs of a strategist. For the purposes of demonstration and clarity, this study utilized a relatively small decision space. Only six critical nodes, pipelines, and storage facilities entered consideration. Furthermore, the assigned priority of these facilities refined the decision space to limit the factor levels rather than assessing the full combinatorial decision space. Instead of interdicting the most critical storage location as the initial factor level, the strategist may require a strategy that assesses each possible combination at every factor level. The 784 runs tested in experiment 3 would quickly become 27,783 potential courses of action requiring 111,132 model runs. Implementation of experiment 3 using 4 replications requires 784 model runs. This automated model with a CPLEX solver needed 8327 seconds to run to completion using an AMD Athlon II X2 215 2.7 GHz Processor, which equates to 2 hours, 18 minutes. Running the full factor combinations would require over 327 hours (2 weeks) using the same processor in order to calculate every combination within the current decision space. Expanding the decision space beyond the 6 critical nodes would further exacerbate this issue. Implementation of the automation in a supercomputer is a realistic method

of exploring such a large decision space. An implementation in a high performance computing environment would provide a potential area of future study for similar problems and allow a decision maker to explore a large decision space in a much shorter amount of time.

5.4 Conclusions

The versatility of this methodology and its automated solution allow a modeler to consider a large decision space within the confines of a network. The methodology can expand to a larger network and that includes multiple countries, smaller regions, and more fully integrated dependent systems. Sufficient data regarding distribution could extend the supply chain through independent consumers such as airports or power plants.

This study provides a basis for determining the functionality of a petroleum product distribution network and measuring impacts to dependent industries. Augmentations to this type of network could inform interdiction strategies through sound experimentation plans.

Using data sets with improved resolution and completeness enables the most accurate constraint set and precise network topography when contemplating an experimental analysis of interdiction strategies. The analyst or campaign planner is well advised to consider collecting the necessary information on an economy or network of interest as early as possible. The planner should also consider updating this information for consistency and accuracy as intelligence improves in order to provide rapid feedback on the effectiveness of an interdiction strategy. The construction of network topography, an informed experimentation plan, and possession of current intelligence data including regional input-output analysis will enable a rapid and consistent recommendation to a decision maker who requires a comprehensive assessment of an interdiction strategy. Given adequate information, a variety of strategies and scenarios may receive substantial investigation prior to operations.

Appendix A. MATLAB 2014 and CPLEX (V 12.5) Implementation

```
%Required inputs include ArcFO, DSS, Dem, ArcCap
%ArcFO is the incidence matrix of the distribution network
%DSS is the storage quantity based on distance from supply points
%Dem is the demand data
%ArcCap is the capacities of the pipelines
A = ArcFO;
[m,n]=size(A);
%Set number of Products
p = 4;
%Introduces the number of supply points to adjust matrices
numSP = 10;
SP = n-numSP;

%Storage Capacity Builder
%Inaccessible Lower Bound
PercLB = .2;
%Safety stock and Safety Fill Factor
SSF = 1.05;
%Storage Capacity Design uses Cycle Time (DSS) in days distance from
Supply
StorCap = SSF * Dem * diag(DSS(:, :));
% Inaccessible Tank Bottoms
LBStorCap = PercLB * StorCap;

%Set Initial Storage
PercIstor = .5;
Istor = PercIstor * StorCap;
StorInt = StorCap;
LBStorInt = LBStorCap;

%Matrix Build of Flow Constraints for each node Set and product type
AFO = [A zeros(m,n) zeros(m,n) zeros(m,n);
        zeros(m,n) A zeros(m,n) zeros(m,n);
        zeros(m,n) zeros(m,n) A zeros(m,n);
        zeros(m,n) zeros(m,n) zeros(m,n) A];
%Q*Demand decision matrix for each product type
DemQ = [diag(Dem(1,:)) zeros(m,m) zeros(m,m) zeros(m,m);
        zeros(m,m) diag(Dem(2,:)) zeros(m,m) zeros(m,m);
        zeros(m,m) zeros(m,m) diag(Dem(3,:)) zeros(m,m);
        zeros(m,m) zeros(m,m) zeros(m,m) diag(Dem(4,:))];
%Flow Equation LHS
FOEq = [AFO -DemQ zeros(m*p) zeros(m*p)];
%Flow Equation RHS
FOEqC = [zeros(1,m*p)];

%Storage recalculation
%Storage Adjustments at each node
DeltaStor = diag(ones(1,m*p));
SlackDem = diag(ones(m*p,1));

%(Can also be specified by type/location using MTX)
MPercIstor = diag(PercIstor(:, :));
```



```

%Istor = MPercIstor * StorCap;
MGAvail = 0;
%Storage Adjustment Flow Balance Equality LHS
StorAdjEq = [zeros(m*p,n*p) DemQ -DeltaStor SlackDem];
%Demand Requirements for each of 4 Products Storage Adj RHS
DemC = [Dem(1,:) Dem(2,:) Dem(3,:) Dem(4,:)];

%Storage Capacity Constraints LHS
StorC = [zeros(m*p,n*p) zeros(m*p) DeltaStor zeros(m*p)];

%Arc Flow Constraints LHS
SumArcFO = [zeros(n-numSP,n-SP) diag(ones(1,n-numSP)) zeros(n-numSP,n-
SP) diag(ones(1,n-numSP)) zeros(n-numSP,n-SP) diag(ones(1,n-numSP))
zeros(n-numSP,n-SP) diag(ones(1,n-numSP))];
SumFO = [SumArcFO zeros(n-numSP,m*p) zeros(n-numSP,m*p) zeros(n-
numSP,m*p);
-SumArcFO zeros(n-numSP,m*p) zeros(n-numSP,m*p) zeros(n-
numSP,m*p)];

%Initialize Daily Values
StorAdj = zeros(p,m);
Shortfall = zeros(m*p,1);

for d = 1:7
% Adjust storage capacity from previous day's numbers
Istor = Istor + StorAdj;
%Storage Capacity Constraints RHS
StorA = [StorCap] - [Istor];
StorAinv = [Istor]-[LBStorCap];
StorMax = [StorA(1,:) StorA(2,:) StorA(3,:) StorA(4,:)];
StorMin = [StorAinv(1,:) StorAinv(2,:) StorAinv(3,:) StorAinv(4,:)];

%Arc Flow Constraints RHS
UBArcC = ArcCap(1,:);
LBArcC = ArcCap(2,:);
BArcC = [UBArcC -LBArcC];

%Supply Availability Constraint LHS

%Supply Constraint RHS
SupC = [Supply(1,:) inf(1,n-numSP) Supply(2,:) inf(1,n-numSP)
Supply(3,:) inf(1,n-numSP) Supply(4,:) inf(1,n-numSP)];
% Constraint Functions to load CPLEX

Aeq = [FOEq; StorAdjEq];
beq = [FOEqC DemC]';

Aineq = [SumFO; StorC; -StorC];
bineq = [BArcC StorMax StorMin]';

```

```

f = [zeros(1,n*p) QW(1,:) QW(2,:) QW(3,:) QW(4,:) zeros(1,m*p)
zeros(1,m*p)];
%Upper Bound of Q
UBQ = 2;
LBQ = .8;
ub = [SupC UBQ*ones(1,m*p) inf(1,m*p) DemC]';
lb = [zeros(1,n*p) LBQ*ones(1,m*p) -inf(1,m*p) zeros(1,m*p)]';

% Shortfall must be bounded between zero and demand, as slack cannot
exceed the
% demanded quantity of product supply.

%QDem is initially bounded between zero and two. As the system is
%interdicted, QDem can become negative to denote the removal of
commodities
%from local storage nodes.

Aeq;
beq;

Aineq;
bineq;
addpath('I:\setup\Desktop\CPEX\cplex\matlab\x64_win64')

f = -f;

ub = ub;
lb = lb;

options = cplexoptimset;
options.Display = 'off';

[x, fval, exitflag, output] = cplexlp (f, Aineq, bineq, Aeq, beq,
lb, ub, [ ], options);

fprintf ('\nSolution status = %s \n', output.cplexstatusstring);
fprintf ('Solution value = %f \n', fval);
disp ('Values =');
disp (x');

%Determine how much is added or removed from storage to meet daily
demand
StorAdj1 = zeros(m,1);
StorAdj2 = zeros(m,1);
StorAdj3 = zeros(m,1);
StorAdj4 = zeros(m,1);

```

```

for s = 1:m
StorAdj1(s,1) = x((n*p)+(m*p)+s,1);
StorAdj2(s,1) = x((n*p)+(m*p)+s+m,1);
StorAdj3(s,1) = x((n*p)+(m*p)+s+2*m,1);
StorAdj4(s,1) = x((n*p)+(m*p)+s+3*m,1);
end
StorAdj = [StorAdj1';StorAdj2';StorAdj3';StorAdj4'];

end

IStorInitial = IStor + StorAdj;

%for r = 1:3

for e = 1:784
%Required inputs include ArcFO, DSS, Dem, ArcCap
%ArcFO is the incidence matrix of the distribution network
%DSS is the storage quantity based on distance from supply points
%Dem is the demand data
%ArcCap is the capacities of the pipelines
A = ArcFO;
[m,n]=size(A);
%Set number of Products
p = 4;
%Introduces the number of supply points to adjust matrices
numSP = 10;
SP = n-numSP;

%Storage Capacity Builder
%Inaccessible Lower Bound
PercLB = .2;
%Safety stock and Safety Fill Factor
SSF = 1.05;
%Storage Capacity Design uses Cycle Time (DSS) in days distance from
Supply
StorCap = SSF * Dem * diag(DSS(:,,:));
% Inaccessible Tank Bottoms
LBStorCap = PercLB * StorCap;

%Set Initial Storage
IStor = IStorInitial;
StorInt = StorCap;
LBStorInt = LBStorCap;

%Matrix Build of Flow Constraints for each node Set and product type
AFO = [A zeros(m,n) zeros(m,n) zeros(m,n);
zeros(m,n) A zeros(m,n) zeros(m,n);
zeros(m,n) zeros(m,n) A zeros(m,n);
zeros(m,n) zeros(m,n) zeros(m,n) A];
%Q*Demand decision matrix for each product type
DemQ = [diag(Dem(1,:)) zeros(m,m) zeros(m,m) zeros(m,m);
zeros(m,m) diag(Dem(2,:)) zeros(m,m) zeros(m,m);
zeros(m,m) zeros(m,m) diag(Dem(3,:)) zeros(m,m);

```

```

        zeros(m,m) zeros(m,m) zeros(m,m) diag(Dem(4,:))];
%Flow Equation LHS
FOEq = [AFO -DemQ zeros(m*p) zeros(m*p)];
%Flow Equation RHS
FOEqC = [zeros(1,m*p)];

%Storage recalculation
%Storage Adjustments at each node
DeltaStor = diag(ones(1,m*p));
SlackDem = diag(ones(m*p,1));

%(Can also be specified by type/location using MTX)
MPercIstor = diag(PercIstor(:,:));
Istor = MPercIstor * StorCap;
MGAvail = 0;
%Storage Adjustment Flow Balance Equality LHS
StorAdjEq = [zeros(m*p,n*p) DemQ -DeltaStor SlackDem];
%Demand Requirements for each of 4 Products Storage Adj RHS
DemC = [Dem(1,:) Dem(2,:) Dem(3,:) Dem(4,:)];

%Storage Capacity Constraints LHS
StorC = [zeros(m*p,n*p) zeros(m*p) DeltaStor zeros(m*p)];

%Arc Flow Constraints LHS
SumArcFO = [zeros(n-numSP,n-SP) diag(ones(1,n-numSP)) zeros(n-numSP,n-
SP) diag(ones(1,n-numSP)) zeros(n-numSP,n-SP) diag(ones(1,n-numSP))
zeros(n-numSP,n-SP) diag(ones(1,n-numSP))];
SumFO = [SumArcFO zeros(n-numSP,m*p) zeros(n-numSP,m*p) zeros(n-
numSP,m*p);
-SumArcFO zeros(n-numSP,m*p) zeros(n-numSP,m*p) zeros(n-
numSP,m*p)];

%Create a Beta and Exp Distribution for Storage Interdiction Time
aS = 4;
bS = 7;
cS = 14;
muS = (aS+4*bS+cS)/6;
if bS-muS == 0
bS=bS-1;
end

muS = (aS+4*bS+cS)/6;

alpha1S = ((muS-aS)*(2*bS-aS-cS))/((bS-muS)*(cS-aS));
alpha2S = (alpha1S*(cS-muS))/(muS-aS);

pdS = makedist('Beta','a',alpha1S,'b',alpha2S);
downtimeS1 = random(pdS)*(cS-aS)+aS;
downtimeS2 = random(pdS)*(cS-aS)+aS;
downtimeS3 = random(pdS)*(cS-aS)+aS;
downtimeS4 = random(pdS)*(cS-aS)+aS;
downtimeS5 = random(pdS)*(cS-aS)+aS;
downtimeS6 = random(pdS)*(cS-aS)+aS;

```

```

pdeS1 = makedist('Exponential','mu', downtimeS1);
pdeS2 = makedist('Exponential','mu', downtimeS2);
pdeS3 = makedist('Exponential','mu', downtimeS3);
pdeS4 = makedist('Exponential','mu', downtimeS4);
pdeS5 = makedist('Exponential','mu', downtimeS5);
pdeS6 = makedist('Exponential','mu', downtimeS6);

recoveryS1 = random(pdeS1);
recoveryS2 = random(pdeS2);
recoveryS3 = random(pdeS3);
recoveryS4 = random(pdeS4);
recoveryS5 = random(pdeS5);
recoveryS6 = random(pdeS6);

%Create Beta and Exp Distribution Random # for Arc Restoration
aA = 7;
bA = 14;
cA = 30;
muA = (aA+4*bA+cA)/6;
if bA-muA == 0
bA=bA-1;
end
bA = bA;
muA = (aA+4*bA+cA)/6;

alpha1A = ((muA-aA)*(2*bA-aA-cA))/((bA-muA)*(cA-aA));
alpha2A = (alpha1A*(cA-muA))/(muA-aA);

pdA = makedist('Beta','a',alpha1A,'b',alpha2A);

downtimeA1 = random(pdA)*(cA-aA)+aA;
downtimeA2 = random(pdA)*(cA-aA)+aA;
downtimeA3 = random(pdA)*(cA-aA)+aA;
downtimeA4 = random(pdA)*(cA-aA)+aA;
downtimeA5 = random(pdA)*(cA-aA)+aA;
downtimeA6 = random(pdA)*(cA-aA)+aA;

pdeA1 = makedist('Exponential','mu', downtimeA1);
pdeA2 = makedist('Exponential','mu', downtimeA2);
pdeA3 = makedist('Exponential','mu', downtimeA3);
pdeA4 = makedist('Exponential','mu', downtimeA4);
pdeA5 = makedist('Exponential','mu', downtimeA5);
pdeA6 = makedist('Exponential','mu', downtimeA6);

recoveryA1 = random(pdeA1);
recoveryA2 = random(pdeA2);
recoveryA3 = random(pdeA3);
recoveryA4 = random(pdeA4);
recoveryA5 = random(pdeA5);
recoveryA6 = random(pdeA6);

%Create Beta and Exp Distribution Random # for Refinery Restoration

```

```

aR = 10;
bR = 21;
cR = 30;
muR = (aR+4*bR+cR)/6;
if bR-muR == 0
bR=bR-1;
end
bR = bR;
muR = (aR+4*bR+cR)/6;

alpha1R = ((muR-aR)*(2*bR-aR-cR))/((bR-muR)*(cR-aR));
alpha2R = (alpha1R*(cR-muR))/(muR-aR);

pdR = makedist('Beta','a',alpha1R,'b',alpha2R);

% Determine Percentage of Gasoline Production remaining after
Interdiction
PGPub = .25;
pdPGP = makedist('Uniform','Lower',0,'Upper',PGPub);
PGP = random(pdPGP);

%Variables for Interdiction or Embargo of Imports, Min/Max
effectiveness
aI = .75;
bI = .9;
%Uniform Distribution used to determine success level of Trade
%Embargo/Blockade
pdI = makedist('Uniform','Lower',aI,'Upper',bI);
Imp = 1-random(pdI);

downtimeR1 = random(pdR)*(cR-aR)+aR;
downtimeR2 = random(pdR)*(cR-aR)+aR;
downtimeR3 = random(pdR)*(cR-aR)+aR;
downtimeR4 = random(pdR)*(cR-aR)+aR;
downtimeR5 = random(pdR)*(cR-aR)+aR;
downtimeR6 = random(pdR)*(cR-aR)+aR;

pdeR1 = makedist('Exponential','mu',downtimeR1);
pdeR2 = makedist('Exponential','mu',downtimeR2);
pdeR3 = makedist('Exponential','mu',downtimeR3);
pdeR4 = makedist('Exponential','mu',downtimeR4);
pdeR5 = makedist('Exponential','mu',downtimeR5);
pdeR6 = makedist('Exponential','mu',downtimeR6);

recoveryR1 = random(pdeR1);
recoveryR2 = random(pdeR2);
recoveryR3 = random(pdeR3);
recoveryR4 = random(pdeR4);
recoveryR5 = random(pdeR5);
recoveryR6 = random(pdeR6);

```

```

%Initialize Daily Values
StorAdj = zeros(p,m);
Shortfall = zeros(m*p,1);

for d = 1:90
% Adjust storage capacity from previous day's numbers
IStor = IStor + StorAdj;

%Interdiction of Storage nodes

if EXPMT(e,2) > 6
    if d < downtimeS1

        %Node 9; Saltillo

        IStor(1:p,13)=0;
        StorCap(1:p,13) = 0;
        LBStorCap(1:p,13) = 0;

    elseif d < downtimeS1 + recoveryS1

        StorCap(1:p,13) = .33*StorInt(1:p,13);
        LBStorCap(1:p,13) = 0;

    elseif d < downtimeS1 + (2*recoveryS1)

        StorCap(1:p,13) = .67*StorInt(1:p,13);
        LBStorCap(1:p,13) = 0;

    else

        StorCap(1:p,13) = StorInt(1:p,13);
        LBStorCap(1:p,13) = 0;

    end

end

end

if EXPMT(e,2) > 3
    if d < downtimeS2

        %node 11 Moclova

        IStor(1:p,15)=0;
        StorCap(1:p,15) = 0;
        LBStorCap(1:p,15) = 0;

```

```

elseif d < downtimeS2 + recoveryS2

    StorCap(1:p,15) = .33*StorInt(1:p,15);
    LBStorCap(1:p,15) = 0;

elseif d < downtimeS2 + (2*recoveryS2)

    StorCap(1:p,15) = .67*StorInt(1:p,15);
    LBStorCap(1:p,15) = 0;

else

    StorCap(1:p,15) = StorInt(1:p,15);
    LBStorCap(1:p,15) = 0;

end

end

if EXPMT(e,2) > 1
    if d < downtimeS3

        % Node 13; Juarez

        IStor(1:p,17)=0;
        StorCap(1:p,17) = 0;
        LBStorCap(1:p,17) = 0;

    elseif d < downtimeS3 + recoveryS3

        StorCap(1:p,17) = .33*StorInt(1:p,17);
        LBStorCap(1:p,17) = 0;

    elseif d < downtimeS3 + (2*recoveryS3)

        StorCap(1:p,17) = .67*StorInt(1:p,17);
        LBStorCap(1:p,17) = 0;

    else

        StorCap(1:p,17) = StorInt(1:p,17);
        LBStorCap(1:p,17) = 0;

    end

end

end

if EXPMT(e,2) > 2

```



```

if d < downtimeS4

    % Node 38: Veracruz

    IStor(1:p,46)=0;
    StorCap(1:p,46) = 0;
    LBStorCap(1:p,46) = 0;

elseif d < downtimeS4 + recoveryS4

    StorCap(1:p,46) = .33*StorInt(1:p,46);
    LBStorCap(1:p,46) = 0;

elseif d < downtimeS4 + (2*recoveryS4)

    StorCap(1:p,46) = .67*StorInt(1:p,46);
    LBStorCap(1:p,46) = 0;

else

    StorCap(1:p,46) = StorInt(1:p,46);
    LBStorCap(1:p,46) = 0;

end

end

if EXPMT(e,2) > 4
    if d < downtimeS5

        %Node 24: SanLuis Potosi

        IStor(1:p,59)=0;
        StorCap(1:p,59) = 0;
        LBStorCap(1:p,59) = 0;

    elseif d < downtimeS5 + recoveryS5

        StorCap(1:p,59) = .33*StorInt(1:p,59);
        LBStorCap(1:p,59) = 0;

    elseif d < downtimeS5 + (2*recoveryS5)

        StorCap(1:p,59) = .67*StorInt(1:p,59);
        LBStorCap(1:p,59) = 0;
    end
end

```

```

else

    StorCap(1:p,59) = StorInt(1:p,59);
    LBStorCap(1:p,59) = 0;

end

end

if EXPMT(e,2) > 5
    if d < downtimeS6

        %Node 36: Puebla

        IStor(1:p,75)=0;
        StorCap(1:p,75) = 0;
        LBStorCap(1:p,75) = 0;

    elseif d < downtimeS6 + recoveryS6

        StorCap(1:p,75) = .33*StorInt(1:p,75);
        LBStorCap(1:p,75) = 0;

    elseif d < downtimeS6 + (2*recoveryS6)

        StorCap(1:p,75) = .67*StorInt(1:p,75);
        LBStorCap(1:p,75) = 0;

    else

        StorCap(1:p,75) = StorInt(1:p,75);
        LBStorCap(1:p,75) = 0;

    end

end

end

%Storage Capacity Constraints RHS
StorA = [StorCap] - [IStor];
StorAinv = [IStor]-[LBStorCap];
StorMax = [StorA(1,:) StorA(2,:) StorA(3,:) StorA(4,:)];
StorMin = [StorAinv(1,:) StorAinv(2,:) StorAinv(3,:) StorAinv(4,:)];

%Arc Flow Constraints RHS
UBArcC = ArcCap(1,:);
LBArcC = ArcCap(2,:);

```

```

% Interdiction of Arc Capacity
if EXPMT(e,3) > 1

%Saltillo
    if d < downtimeA1
        UBArcC(1,9) = 0;
        LBArcC(1,9) = 0;

        elseif d < downtimeA1 + recoveryA1
            UBArcC(1,9) = .5*UBArcC(1,9);
            LBArcC(1,9) = .5*LBArcC(1,9);

            elseif d < downtimeA1 + (2*recoveryA1)
                UBArcC(1,9) = .75*UBArcC(1,9);
                LBArcC(1,9) = .75*LBArcC(1,9);
            else

        end
    end

if EXPMT(e,3) > 4
    %Moclova
    if d < downtimeA2
        UBArcC(1,14) = 0;
        LBArcC(1,14) = 0;
        elseif d < downtimeA2 + recoveryA2
            UBArcC(1,14) = .5*UBArcC(1,14);
            LBArcC(1,14) = .5*LBArcC(1,14);

            elseif d < downtimeA2 + (2*recoveryA2)
                UBArcC(1,14) = .75*UBArcC(1,14);
                LBArcC(1,14) = .75*LBArcC(1,14);
            else

        end
    end

if EXPMT(e,3) > 6
    %Juarez
    if d < downtimeA3
        UBArcC(1,13) = 0;
        LBArcC(1,13) = 0;

        elseif d < downtimeA3 + recoveryA3
            UBArcC(1,13) = .5*UBArcC(1,13);
            LBArcC(1,13) = .5*LBArcC(1,13);

            elseif d < downtimeA3 + (2*recoveryA3)
                UBArcC(1,13) = .75*UBArcC(1,13);
                LBArcC(1,13) = .75*LBArcC(1,13);
            else

        end
    end
end

```

```

end

if EXPMT(e,3) > 3
    %Puebla
    if d < downtimeA4
        UBArcC(1,38) = 0;
        LBArcC(1,38) = 0;

        elseif d < downtimeA4 + recoveryA4
            UBArcC(1,38) = .5*UBArcC(1,38);
            LBArcC(1,38) = .5*LBArcC(1,38);

            elseif d < downtimeA4 + (2*recoveryA4)
                UBArcC(1,38) = .75*UBArcC(1,38);
                LBArcC(1,38) = .75*LBArcC(1,38);

            else

        end
    end
end

if EXPMT(e,3) > 2
    %San Luis Potosi
    if d < downtimeA5
        UBArcC(1,53) = 0;
        LBArcC(1,53) = 0;

        elseif d < downtimeA5 + recoveryA5
            UBArcC(1,53) = .5*UBArcC(1,53);
            LBArcC(1,53) = .5*LBArcC(1,53);

            elseif d < downtimeA5 + (2*recoveryA5)
                UBArcC(1,53) = .75*UBArcC(1,53);
                LBArcC(1,53) = .75*LBArcC(1,53);
            else

        end
    end
end

if EXPMT(e,3) > 5
    %Veracruz
    if d < downtimeA6
        UBArcC(1,35) = 0;
        LBArcC(1,35) = 0;
        elseif d < downtimeA6 + recoveryA6
            UBArcC(1,35) = .5*UBArcC(1,35);
            LBArcC(1,35) = .5*LBArcC(1,35);

            elseif d < downtimeA6 + (2*recoveryA6)
                UBArcC(1,35) = .75*UBArcC(1,35);
                LBArcC(1,35) = .75*LBArcC(1,35);
            else

```

```

    end
end

BArcC = [UBArcC -LBArcC];

%Supply Availability Constraint LHS

%SumSupOP = [diag(ones(1,numSP)) zeros(numSP,m-1) diag(ones(1,numSP))
zeros(numSP,m-1) diag(ones(1,numSP)) zeros(numSP,m-1)
diag(ones(1,numSP)) zeros(numSP,m-1)];
%bineq = [Supply(1,:) Supply(2,:) Supply(3,:) Supply(4,:)]';
%Supply Constraint RHS
SupC = [Supply(1,:) inf(1,n-numSP) Supply(2,:) inf(1,n-numSP)
Supply(3,:) inf(1,n-numSP) Supply(4,:) inf(1,n-numSP)];

%Interdiction of Refinery Supplies
if EXPMT(e,1) > 1
    %Cadereyta
    if d < downtimeR1
        SupC(1,5) = PGP*SupC(1,5);
        SupC(1,92) = 0;
        SupC(1,179) = 0;
        SupC(1,266) = 0;

        elseif d < downtimeR1 + recoveryR1
            SupC(1,5) = .25*SupC(1,5);
            SupC(1,91) = .25*SupC(1,91);
            SupC(1,177) = .25*SupC(1,177);
            SupC(1,263) = .25*SupC(1,263);

            elseif d < downtimeR1 + (2*recoveryR1)
                SupC(1,5) = .50*SupC(1,5);
                SupC(1,91) = .50*SupC(1,91);
                SupC(1,177) = .50*SupC(1,177);
                SupC(1,263) = .50*SupC(1,263);

                elseif d < downtimeR1 + (3*recoveryR1)
                    SupC(1,5) = .75*SupC(1,5);
                    SupC(1,91) = .75*SupC(1,91);
                    SupC(1,177) = .75*SupC(1,177);
                    SupC(1,263) = .75*SupC(1,263);
                else
                    end
            end
end

if EXPMT(e,1) > 3
    %Tula
    if d < downtimeR2
        SupC(1,7) = PGP*SupC(1,7);
        SupC(1,94) = 0;
    end
end

```

```

SupC(1,181) = 0;
SupC(1,268) = 0;

elseif d < downtimeR2 + recoveryR2
SupC(1,7) = .25*SupC(1,7);
SupC(1,93) = .25*SupC(1,93);
SupC(1,179) = .25*SupC(1,179);
SupC(1,265) = .25*SupC(1,265);

elseif d < downtimeR2 + (2*recoveryR2)
SupC(1,7) = .50*SupC(1,7);
SupC(1,93) = .50*SupC(1,93);
SupC(1,179) = .50*SupC(1,179);
SupC(1,265) = .50*SupC(1,265);

elseif d < downtimeR2 + (3*recoveryR2)
SupC(1,7) = .75*SupC(1,7);
SupC(1,91) = .75*SupC(1,91);
SupC(1,179) = .75*SupC(1,179);
SupC(1,265) = .75*SupC(1,265);
else
end
end

if EXPMT(e,1) > 2
    %Minatatlan
    if d < downtimeR3
SupC(1,9) = PGP*SupC(1,9);
SupC(1,95) = 0;
SupC(1,181) = 0;
SupC(1,267) = 0;

elseif d < downtimeR3 + recoveryR3
SupC(1,9) = .25*SupC(1,9);
SupC(1,95) = .25*SupC(1,95);
SupC(1,181) = .25*SupC(1,181);
SupC(1,267) = .25*SupC(1,267);

elseif d < downtimeR3 + (2*recoveryR3)
SupC(1,9) = .50*SupC(1,9);
SupC(1,95) = .50*SupC(1,95);
SupC(1,181) = .50*SupC(1,181);
SupC(1,267) = .50*SupC(1,267);

elseif d < downtimeR3 + (3*recoveryR3)
SupC(1,9) = .75*SupC(1,9);
SupC(1,95) = .75*SupC(1,95);
SupC(1,181) = .75*SupC(1,181);
SupC(1,267) = .75*SupC(1,267);
else
end
end

if EXPMT(e,1) > 4

```

```

%Madero
if d < downtimeR4
SupC(1,6) = PGP*SupC(1,6);
SupC(1,92) = 0;
SupC(1,178) = 0;
SupC(1,264) = 0;

elseif d < downtimeR4 + recoveryR4
SupC(1,6) = .25*SupC(1,6);
SupC(1,92) = .25*SupC(1,92);
SupC(1,178) = .25*SupC(1,178);
SupC(1,264) = .25*SupC(1,264);

elseif d < downtimeR4 + (2*recoveryR4)
SupC(1,6) = .50*SupC(1,6);
SupC(1,92) = .50*SupC(1,92);
SupC(1,178) = .50*SupC(1,178);
SupC(1,264) = .50*SupC(1,264);

elseif d < downtimeR4 + (3*recoveryR4)
SupC(1,6) = .75*SupC(1,6);
SupC(1,92) = .75*SupC(1,92);
SupC(1,178) = .75*SupC(1,178);
SupC(1,264) = .75*SupC(1,264);
else
end
end

if EXPMT(e,1) > 5
%Salina Cruz
if d < downtimeR5
SupC(1,10) = PGP*SupC(1,10);
SupC(1,96) = 0;
SupC(1,182) = 0;
SupC(1,268) = 0;

elseif d < downtimeR5 + recoveryR5
SupC(1,10) = .25*SupC(1,10);
SupC(1,96) = .25*SupC(1,96);
SupC(1,182) = .25*SupC(1,182);
SupC(1,268) = .25*SupC(1,268);

elseif d < downtimeR5 + (2*recoveryR5)
SupC(1,10) = .50*SupC(1,10);
SupC(1,96) = .50*SupC(1,96);
SupC(1,182) = .50*SupC(1,182);
SupC(1,268) = .50*SupC(1,268);

elseif d < downtimeR5 + (3*recoveryR5)
SupC(1,10) = .75*SupC(1,10);
SupC(1,96) = .75*SupC(1,96);
SupC(1,182) = .75*SupC(1,182);
SupC(1,268) = .75*SupC(1,268);
else

```

```

    end
end

if EXPMT(e,1) > 6
    %Salamanca
    if d < downtimeR6
        SupC(1,8) = PGP*SupC(1,8);
        SupC(1,94) = 0;
        SupC(1,180) = 0;
        SupC(1,266) = 0;

        elseif d < downtimeR6 + recoveryR6
            SupC(1,8) = .25*SupC(1,8);
            SupC(1,94) = .25*SupC(1,94);
            SupC(1,180) = .25*SupC(1,180);
            SupC(1,266) = .25*SupC(1,266);

            elseif d < downtimeR6 + (2*recoveryR6)
                SupC(1,8) = .50*SupC(1,8);
                SupC(1,94) = .50*SupC(1,94);
                SupC(1,180) = .50*SupC(1,180);
                SupC(1,266) = .50*SupC(1,266);

                elseif d < downtimeR6 + (3*recoveryR6)
                    SupC(1,8) = .75*SupC(1,8);
                    SupC(1,94) = .75*SupC(1,94);
                    SupC(1,180) = .75*SupC(1,180);
                    SupC(1,266) = .75*SupC(1,266);
                else
                    end
            end
end

%Eliminate Percentage of Imported Middle Distillate Supply

if d < 60
    if EXPMT(e,4) > 1
        %import point 1
        SupC(1,88) = Imp*SupC(1,88);
        SupC(1,175) = Imp*SupC(1,175);
        SupC(1,262) = Imp*SupC(1,262);
        end

        if EXPMT(e,4) > 3
            %Import point 3
            SupC(1,90) = Imp*SupC(1,90);
            SupC(1,177) = Imp*SupC(1,177);
            SupC(1,264) = Imp*SupC(1,264);

            end

        if EXPMT(e,4) > 2
            %import point 4

```



```

    SupC(1,91) = Imp*SupC(1,91);
    SupC(1,178) = Imp*SupC(1,178);
    SupC(1,265) = Imp*SupC(1,265);
end
end
% Constraint Functions to load CPLEX

Aeq = [FOEq; StorAdjEq];
beq = [FOEqC DemC]';

Aineq = [SumFO; StorC; -StorC];
bineq = [BArcC StorMax StorMin]';

f = [zeros(1,n*p) QW(1,:) QW(2,:) QW(3,:) QW(4,:) zeros(1,m*p)
zeros(1,m*p)];
%Upper Bound of Q
UBQ = 2;
LBQ = -1;

ub = [SupC UBQ*ones(1,m*p) inf(1,m*p) DemC]';
lb = [zeros(1,n*p) LBQ*ones(1,m*p) -inf(1,m*p) zeros(1,m*p)]';

% Shortfall must be bounded between zero and demand, as slack cannot
exceed the
% demanded quantity of product supply.

%QDem is initially bounded between zero and two. As the system is
%interdicted, QDem can become negative to denote the removal of
commodities
%from local storage nodes.

Aeq;
beq;

Aineq;
bineq;
addpath('I:\setup\Desktop\CPEX\cplex\matlab\x64_win64')

f = -f;

ub = ub;
lb = lb;

options = cplexoptimset;
options.Display = 'off';

```

```

[x, fval, exitflag, output] = cplexlp (f, Aineq, bineq, Aeq, beq,
lb, ub, [ ], options);

fprintf ('\nSolution status = %s \n', output.cplexstatusstring);
fprintf ('Solution value = %f \n', fval);
disp ('Values =');
disp (x');

%Determine how much is added or removed from storage to meet daily
demand
StorAdj1 = zeros(m,1);
StorAdj2 = zeros(m,1);
StorAdj3 = zeros(m,1);
StorAdj4 = zeros(m,1);

for s = 1:m
StorAdj1(s,1) = x((n*p)+(m*p)+s,1);
StorAdj2(s,1) = x((n*p)+(m*p)+s+m,1);
StorAdj3(s,1) = x((n*p)+(m*p)+s+2*m,1);
StorAdj4(s,1) = x((n*p)+(m*p)+s+3*m,1);
end
StorAdj = [StorAdj1';StorAdj2';StorAdj3';StorAdj4'];

%Measure the shortfalls of each commodity type
SGas = zeros(m,1);
SDiesel = zeros(m,1);
SJetF = zeros(m,1);
SFOil = zeros(m,1);

for s = 1:m
SGas(s,1) = x((n*p)+(2*m*p)+s,1);
SJetF(s,1) = x((n*p)+(2*m*p)+s+m,1);
SDiesel(s,1) = x((n*p)+(2*m*p)+s+2*m,1);
SFOil(s,1) = x((n*p)+(2*m*p)+s+3*m,1);

end
Shortfall = Shortfall + [SGas; SJetF; SDiesel; SFOil];

if d < 21
MGCrit = IStor(2,13) + IStor(3,13) + IStor(2,15) + IStor(3,15) +
IStor(2,17) + IStor(3,17) + IStor(2,46) + IStor(3,46) + IStor(2,59) +
IStor(3,59) + IStor(2,75) + IStor(3,75);
UASTor = LBStorCap(2,13) + LBStorCap(3,13) + LBStorCap(2,15) +
LBStorCap(3,15) + LBStorCap(2,17) + LBStorCap(3,17) + LBStorCap(2,46) +
LBStorCap(3,46) + LBStorCap(2,59) + LBStorCap(3,59) + LBStorCap(2,75) +
LBStorCap(3,75);
else
MGCrit = 0;
UASTor = 0;

```

```

end
MGAvail = MGAvail + (MGCrit - UASTor);

end
EXPMT(e,6) = MGAvail;
IStor';
Shortfall';

    GShortfall = 0;
    JShortfall = 0;
    DShortfall = 0;
    FShortfall = 0;

for g = 1:m
    GShortfall = Shortfall(g,1) + GShortfall;
    JShortfall = Shortfall(g+m,1) + JShortfall;
    DShortfall = Shortfall(g+2*m,1) + DShortfall;
    FShortfall = Shortfall(g+3*m,1) + FShortfall;
end

TOTALS = [GShortfall;
    JShortfall;
    DShortfall;
    FShortfall];
SUMTOTAL = GShortfall + JShortfall + DShortfall + FShortfall;
VALLOST = 100*TOTALS' * PRICE;
EXPMT(e,5) = VALLOST;
EXPMT(e,7) = SUMTOTAL;

end
    %if r == 1
    %EXPMT1 = EXPMT;
    %elseif r == 2
    % EXPMT2 = EXPMT;
    %elseif r == 3
    % EXPMT3 = EXPMT;
    % else
    % end
%end

PCDG = [zeros(784,32)];
PercDeg = [zeros(1,32)];

for j = 1:784

[m,n] = size(aij);
I = eye(m);
IO = (I-aij);
Resource = rij;
ConsOP = C;
ExRes = P;

```

```

VALLOST = 4*EXPMT(j,5)/1000000;
Aineq = [IO;Resource; -IO];
bineq = [ConsOP; ExRes; zeros(m,1)];
fbuild = MaxOP;

f = [ones(1,n)];

ub = [inf(1,n)];
ub(1,7) = 275482.846-VALLOST;
lb = [zeros(1,n)];

Aineq;
bineq;
addpath('I:\setup\Desktop\CPEX\cplex\matlab\x64_win64')

f = -f;

ub = ub;
lb = lb;

options = cplexoptimset;
options.Display = 'on';

[x, fval, exitflag, output] = cplexlp (f, Aineq, bineq, [],[], lb,
ub, [ ], options);

fprintf ('\nSolution status = %s \n', output.cplexstatusstring);
fprintf ('Solution value = %f \n', fval);
disp ('Values =');
disp (x');

for g = 1:m
PercDeg(1,g) = x(g,1)/MaxOP(1,g);
PCDG(j,g) = PercDeg(1,g);
end

end

```

Appendix B. Mexico Input-Output Model (OECD, 2014)

Country		Mexico															
Variable		Total															
Period		Period mid- 2000s															
Currency		National currency, million															
Column Sector		C0105 Agriculture, hunting, forestry and fishing	C10114 Mining and quarrying	C15116 Food products, beverages and tobacco	C17119 Textiles, textile products, leather and footwear	C20 Wood and products of wood and cork	C21122 Pulp, paper, paper products, printing and publishing	C23 Coke, refined petroleum products and nuclear fuel	C24 Chemicals and chemical products	C25 Rubber and plastics products	C26 Other non-metallic mineral products	C27 Basic metals	C28 Fabricated metal products except machinery and equipment	C29 Machinery and equipment n.e.c.	C30 Office, accounting and computing machinery	C31 Electrical machinery and apparatus n.e.c.	C34 Motor vehicles, trailers and semi-trailers
Row Sector	1																
C0105 Agriculture, hunting, forestry and fishing		50573.06669	1.740573509	194206.9139	9656.789339	9509.756321	32.89344964	10.5313423	1794.674451	487.2864306	441.3841074	1.729945648	13.63495862	3.060514285	29.11387825	8.003124928	150.4099937
C10114 Mining and quarrying		106.3086275	7672.073741	1126.817217	118.6776672	9.00774192	90.11421542	158712.152	88475.4184	59.37414437	11333.07001	17781.94064	83.34216195	243.0568374	169.3435244	157.7253221	197.9369063
C15116 Food products, beverages and tobacco		33278.70853	222.4224148	112593.0889	4705.413385	49.58915033	491.788614	81.36711771	1554.487224	211.4776355	226.2023401	232.9115405	170.2447114	111.3816414	419.46996	126.1243724	673.4221462
C17119 Textiles, textile products, leather and footwear		903.2449808	54.22247439	2330.710955	79273.20545	132.6317463	3043.748469	178.6388905	979.113383	2440.670473	770.6688505	1173.420218	982.9575459	765.5737187	4389.815117	2009.990154	18670.15176
C20 Wood and products of wood and cork		270.0815135	767.993507	225.7208165	217.022106	4941.40219	209.4566048	39.65836178	209.1006837	145.3766916	487.1625708	185.2983322	247.5225715	133.2213812	2828.137087	535.8995913	1112.234028
C21122 Pulp, paper, paper products, printing and publishing		965.353492	52.070117	11184.76253	3047.020244	167.8005319	28425.38177	232.2107127	3837.065585	2057.763857	2950.115592	504.5391518	1162.283422	732.8469199	6776.53662	2375.742963	3267.299007
C23 Coke, refined petroleum products and nuclear fuel		353.1194083	4332.049779	7657.266447	1133.851069	462.3523855	1132.60416	2315.84744	5998.894051	593.5326973	4082.520309	5788.292981	719.1725868	291.9824433	476.6467999	649.569077	1625.490759
C24 Chemicals and chemical products		18213.78528	2011.01527	18302.61746	6596.565292	614.5484452	6344.247268	12414.42034	78689.4711	25463.03578	6325.177325	2967.954309	2552.560789	2374.082346	10722.26421	4606.442874	11384.16014
C25 Rubber and plastics products		3018.139745	320.9994708	16296.01777	4556.673951	182.1514695	2888.488864	571.7991339	2986.196563	6166.750087	1050.778063	691.4366645	2322.666939	2201.530177	20218.55091	8938.874702	33037.23754
C26 Other non-metallic mineral products		77.98714805	1828.781013	6854.204878	215.7727714	111.4666305	293.1406389	33.40244594	754.4315694	268.1979401	9949.711254	529.3664988	935.4016745	367.4280174	4456.650472	1777.297413	4315.423115
C27 Basic metals		266.2813232	4846.538984	316.3334701	636.2479589	72.12281375	352.1596204	159.6858557	782.4001202	2658.223054	1531.31838	58718.31183	27599.18535	8777.379008	14161.96744	18143.16468	30248.62506
C28 Fabricated metal products except machinery and equipment		1909.938667	934.0410399	3328.979407	1455.718712	233.5434263	347.2442791	1581.655908	964.7715599	2044.661488	637.2068812	1349.103729	8297.966296	3229.906463	8120.227125	6349.4181	17405.17423
C29 Machinery and equipment n.e.c.		250.0468611	873.0519691	881.7343191	949.887385	139.1066306	365.1814676	1333.146688	576.9629995	1028.441234	409.1192599	896.107605	1809.485291	6103.032444	6161.756719	3335.181306	7811.571331
C30 Office, accounting and computing machinery		168.29856	167.4600983	970.0987219	1518.893112	73.88186452	1015.891186	339.6531654	2007.025641	2946.994396	1313.224028	692.3255087	2603.204696	4778.872817	203518.9994	14870.45645	27128.53887
C31 Electrical machinery and apparatus n.e.c.		137.0783431	120.8408624	359.7249389	1353.797308	43.92117501	515.8557708	198.3469301	409.4814834	2307.061683	644.5443374	1060.946107	2447.888499	4026.921699	43535.59314	22973.5716	32977.96282
C34 Motor vehicles, trailers and semi-trailers		1672.673911	1427.65153	5354.29756	2886.779074	169.1247678	1213.187231	318.8812865	1695.648851	1846.351952	1710.988447	3018.384417	1943.31878	1634.801007	5471.579101	3015.455214	152776.1423
C36373 Manufacturing n.e.c. recycling		201.3410011	166.0133463	1011.176253	2341.831866	134.8780592	525.1204455	92.9816872	1296.647156	798.7936272	573.2611519	425.7548908	655.0079865	404.1344459	3648.69346	1538.549943	1825.461108
C40141 Electric ty, gas and water supply		5027.762336	2897.385138	11563.41046	3273.396217	499.8228793	2631.504707	312.5289145	3604.895933	2409.886999	3896.504686	7353.543426	1577.813982	690.7579501	2703.527529	1604.289282	3932.282046
C45 Construction		910.9032244	348.4826271	2263.26349	226.638193	7.590042079	63.18903907	643.460937	452.5146759	145.5414288	250.9638007	85.36795117	117.3318496	59.98613151	615.3306974	407.911531	854.7626121
C50752 Wholesale and retail trade repairs		24570.81105	13669.6079	83341.37126	14882.00011	3169.654733	10571.71104	4960.202179	28002.5638	9473.699904	11476.8404	21137.58392	9285.679308	5709.874026	14461.54121	8374.349914	68811.7303
C55 Hotels and restaurants		72.84568803	1172.417603	1263.111757	1421.840272	52.21343678	241.5382754	99.22223937	1352.849521	468.8634808	264.6441945	218.9887602	508.2352426	341.3550254	2642.099948	1028.037019	2636.539069
C60163 Transport and storage		8608.568357	5532.498679	28722.76181	5333.030579	1355.977349	4698.763736	1620.399426	9518.048579	3608.090091	3685.673528	4846.22699	2525.420064	1854.632629	7643.99178	3552.543798	16619.57422
C64 Post and telecommunications		1463.901657	1077.308956	6373.5923	964.7072113	132.3793761	977.9292557	306.8365736	6170.627863	618.8348689	922.5928186	214.8736137	789.2926853	419.2675888	1522.468985	493.7081326	3020.409948
C65167 Finance and insurance		5730.628067	12378.11491	6319.967279	1142.604152	108.9006636	1298.886965	1482.458624	4227.313375	535.1067287	1375.845904	966.9299702	896.3420306	478.9991371	550.5699741	467.9309325	2954.728976
C70 Real estate activities		108.0383124	358.0641888	5163.963479	2467.565946	196.1869351	1519.700317	198.874583	2184.31626	1755.096693	1247.883261	470.4488433	1262.037142	686.5959553	2053.981903	1268.971905	2290.269479
C71 Renting of machinery and equipment		851.6396777	8365.274834	4171.706138	449.2565722	20.23863228	668.1097482	157.4231763	3367.896969	609.978113	891.1278339	223.2468874	332.1833408	772.1682878	1606.534074	499.9129426	3267.126328
C72 Computer and related activities		17.91310126	19.2425037	82.97530642	15.30530366	1.940599632	11.66638215	3.466236702	29.41295035	11.77961858	9.22501443	4.115085485	11.68295978	8.579490523	16.71383128	5.984403226	15.13581396
C74 Other Business Activities		5867.145984	10237.37964	30753.92364	7414.378734	425.1069233	4857.978512	12941.00075	16645.93949	4926.813692	6513.843371	3593.064562	4043.518481	2797.77532	10153.15277	3557.287596	11647.85169
C75 Public admin. n. and defence; compulsory social security		0.239	0.031	0	0	0	0	0	0	0	0	0	0	0.137	0	0	0
C80 Education		0.919370761	1.700074886	112.00996	12.10260036	0.672995181	17.06053494	4.12584826	157.5607006	6.22091987	17.73951995	1.944669766	8.201468107	5.296089393	10.99205506	7.182307205	61.21619245
C85 Health and social work		12.35638504	6.701690592	48.19431693	10.72743656	1.889756821	6.857780731	2.686730282	17.15864015	6.681725053	6.46204738	10.37319651	6.075513996	3.617574857	10.17266162	5.668851734	38.05036861
C90793 Other community, social and personal services		45.80025991	274.4119478	224.7964779	38.9480195	4.192790763	46.98495155	8.596515269	113.085911	27.07934671	32.00783524	19.56530566	19.2687091	24.41296385	61.37820998	29.83165885	115.2482987
Domestic purchases by non-residents		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Non-comparable imports (cif/FOB adj.)		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Direct purchases abroad by residents		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Total Imports		59499.256	10852.999	84481.445	115179.338	11204.714	51746.998	32929.549	211888.122	116410.733	20520.524	94648.721	84680.515	148326.769	383923.134	167072.019	257406.742
Total Intermediate consumption /final use at basic prices		166564.9274	100237.3878	953405.5133	158516.6235	23024.05244	74908.39529	201355.8621	268865.7754	76127.8668	75027.81813	135164.0975	75928.92704	50032.86715	379157.8014	117715.0792	460672.1644
Taxes, less subsidies, on products		1798.624145	1013.264796	1640.86318	1132.775703	157.6371308	404.7546048	638.7870891	1780.546169	292.9029837	970.2463302	1535.325894	340.6995746	250.161514	325.2129851	303.9905052	1531.589287
VALUE Added at basic prices		279600.6177	439201.5894	370036.8844	85265.74584	17044.08043	40421.42409	40558.94778	132993.1805	37027.58222	85213.31554	77290.66458	40350.85939	30266.07333	74602.02058	41394.05088	202929.2614
GOPS Gross Operating Surplus		229272.4097	148659.8764	278267.1244	46737.26684	11336.31943	24369.12209	23305.04778	83815.53846	19733.65022	60978.92954	58009.94658	21871.20939	8200.946333	42445.59558	21561.58588	131423.6564
LABR Compensation of Employees		50211.942	34662.957	89920.16	37749.493	5660.52	15552.005	17206.06	47149.952	16812.949	23891.135	18899.035	17981.395	21674.198	31406.196	19363.695	70576.748
OTXS																	



Cascading Effects of Fuel Network Interdiction

MAJ Jeffrey Painter, USA

Advisor: Dr. Richard F. Deckro, Reader: Lt Col Matthew J.D. Robbins, PhD
Department of Operational Sciences, Air Force Institute of Technology

INTRODUCTION

Theater level strategists have planned interdiction campaigns against adversarial petroleum targets since WWII with mixed results. An operational plan requires the ability to assess the military effectiveness and cascading industrial impacts in the affected economy. The results will assist the decision maker in determining the best courses of action to meet their end state and intent.

PROBLEM STATEMENT

1. Determine how the interdiction of a refined petroleum distribution network impact the delivery of energy products to the end user.

2. Assess how cascading effects manifest throughout various industries of the economy within an impacted country or region.

Describe how military strategists can plan to interdict a refined petroleum network in order to limit the availability of refined products to an adversary while controlling the magnitude of cascading economic impacts to support an operational plan.

Q-Demand Maximum Flow Network Formulation

Given a petroleum product network populated with refinery and import supply points servicing transshipment nodes through a polyduct network, maximize the flow of each product type giving preference to critical locations in order to allow assessment of the impact of disruptions on various network facilities within constraints of the infrastructure. Determine the response of military availability and the value of economic losses through experimentation.

$$\max_{Q_p} \sum_{p \in P} Q_p \quad \text{subject to: } \sum_{p \in P} Q_p \leq \sum_{p \in P} Q_p^{\max} \quad \forall p \in P$$

$$Q_p \leq Q_p^{\max} \quad \forall p \in P$$

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METHODOLOGY

This approach requires development of a network, implementation of an interdiction experimental design, and use of an input-output model to find cascading effects. The results inform a comprehensive strategy decision.



CONTRIBUTIONS

- Effective targeting strategies consider military effectiveness & cascading impacts to support a commander's end-state
- The model can assess a variety of target infrastructure and interdiction strategies
- Versatility allows the analyst to alter parameters as necessary

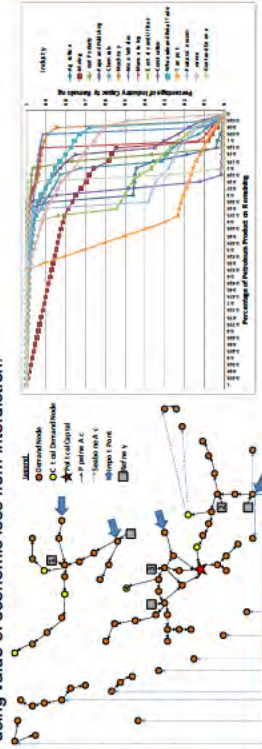
FUTURE RESEARCH

- Extend the network into crude petroleum availability, distribution, and price fluctuation
- Include time dependent modeling for pipeline, refinery, and demand parameters; extend time factors into dynamic I-O Models
- Consider a high-performance computing environment to expand experimental decision space
- Improve experimental design efficiency

DEPARTMENT OF OPERATIONAL SCIENCES

APPLICATION: NATIONAL OIL COMPANY CASE STUDY

A relevant series of scenarios explores the ability of the model to assess the impacts on the capacity of a known refined product supply network within an advanced petroleum infrastructure through experimentation using site specific disruptions against critical locations. An assessment of availability of military grade fuels and resulting economic impacts informs strategic decisions. Input-Output Model determines cascading effects using value of economic loss from interdiction.



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14. ABSTRACT This thesis develops the Fuel Interdiction and Resulting Cascading Effects (FI&RCE) model. The study details the development and experimental testing of a framework for assessing the interdiction of a refined petroleum production and distribution network. FI&RCE uses a maximum flow mathematical programming formulation that models the transit of fuels from points of importation and refinement through a polyduct distribution network for delivery across a range of end user locations. The automated model accommodates networks of varying size and complexity. FI&RCE allows for parameters and factor settings that enable robust experimentation through implementation in MATLAB 2014 and the commercial solver CPLEX (Version 12.5). Experimental design allows the investigation of interdiction or disruption on supply and network infrastructure locations in order to support the strategic analytical needs of the user. Given a target set, FI&RCE provides measured responses for the resulting fuel availability and a valuation of economic loss. The value of economic loss feeds a Leontief based input-output model that assesses the cascading effects in the studied economy by implementing a mathematical program that optimizes the remaining industrial outputs. FI&RCE demonstrates a framework to investigate the military and cascading effects of a fuel interdiction campaign plan using a realistic case study.					
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